LATENT CLASS AND TRANSITION ANALYSIS OF ELEMENTARY SCIENCE STUDENTS' EXPECTANCY-VALUE-COST MOTIVATION

by
David McKinney

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Abstract

The three studies described in this dissertation explored the expectancy-value-cost motivation for science of 1,706 fourth and fifth grade students. Data was collected as part of the STEM Achievement in Baltimore Elementary Schools (SABES) project. Survey data measuring student task expectancy, task value, and perceived cost—important aspects of student motivation that are predictive of achievement, persistence, and choice—were collected in 2015, 2016, and 2017 in 14 schools (12 in 2017). The first two studies utilized latent class analysis to identify intra-individual patterns of these motivation constructs in 860 Black fifth graders and related class membership to student variables and science achievement. A three class model fit the data best and included *High Expectancy and Value* (*High EV,* 73%); *High Values and Perceived Costs, Moderate Expectancy* (*Conflicted,* 17%); and *Low Expectancy and Value* (*Low EV*, 10%) classes. Students receiving special education services were more likely to be in the *Conflicted* class relative to the *High EV* class. Higher prior achievement was predictive of being in the *High EV* class relative to the *Conflicted* class. Membership in the *High EV* class was predictive of the higher subsequent science achievement. Membership in the *Conflicted* class was predictive of lower science achievement. The third study used latent transition analysis to regress latent class membership in fifth grade on membership in fourth grade for 1,706 fourth and fifth graders. A time-invariant three-class model was selected. The latent classes were similar to those described in study 1. Class membership was most stable in the *High EV* class, with 73% of students in this class in fourth grade estimated to be in the same class in fifth grade. The *Conflicted* class was less stable, with 56% of fourth grade members predicted to remain in the class in fifth grade, 37% predicted to transition to the *High EV* class, and 8% to the *Low EV* class. The *Low EV* class was the least stable, with 42% of fourth grade members predicted to remain in the class in fifth grade, 32% predicted to transition to the *High EV* class, and 26% to the *Conflicted* class.

Readers: Jeffrey Grigg, PhD (academic advisor); Douglas MacIver, PhD

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Table of Contents

List of Tables

List of Figures

Chapter 1—Introduction

Improved science education is often at the forefront of education policy discussion in the United States (e.g., National Academy of Sciences, 2006; Obama, 2012; U.S. Department of Education, 2015). This focus, which began in response to Sputnik's successful launch and orbit and has since expanded to STEM (science, technology, engineering, and mathematics) education, calls for increased participation in STEM fields and careers by students once they leave the education system (e.g., R. Atkinson & Mayo, 2010; Change the Equation, 2012; National Academy of Sciences, 2006; U.S. Department of Education, 2015), but also for increased scientific literacy for all students (e.g., American Association for the Advancement of the Sciences, 1993; National Research Council, 2012; Gluckman, 2011; Osborne, 2007). The "careers" goal is in response to the United States' decline in world education rankings in science and mathematics [e.g., the U.S. ranked 18th in science and 29th in mathematics among 35 OECD countries on the 2015 PISA (OECD, 2018)] and a changing economy and job market, in which science-related jobs are increasing at the expense of other professions (e.g., National Academy of Sciences, 2006; U.S. Department of Education, 2015). The "literacy" goal stems from a desire to give all students a quality education that allows them to navigate and participate in an increasingly science- and technology- infused society (e.g., American Association for the Advancement of the Sciences, 1993; National Research Council, 2012; New Zealand et al., 2011).

If both of these goals are to be met, the education system needs to support more than guiding the "motivated" science students into a "STEM pipeline", the term often used to describe the path from secondary science to a STEM-related career (e.g., Maltese & Tai, 2011). Encouraging motivated students into this pipeline and maintaining their motivation is important, to be sure, but what of the "unmotivated" science students—how do we ensure they stay motivated to learn science in order to gain adequate scientific literacy to actively participate in society?

Motivation has been tied to academic achievement, persistence, and academic choices (e.g., Eccles, Adler, Goff, Kaczala, & Midgley, 1983; Guo et al., 2016; Nagengast et al., 2011; Simpkins, Davis-Kean, & Eccles, 2006). Recent randomized control trials (RCT) demonstrated that interventions designed to change motivation not only increase student motivation, but also result in higher achievement and increased course enrollment (e.g. Harackiewicz, Rozek, Hulleman, & Hyde, 2012; Hulleman, Kosovich, Barron, & Daniel, 2017). Thus, motivation could help us understand how to increase STEM participation and achievement in school so students graduate with sufficient science knowledge and understanding to participate in society and the economy.

Most motivation research uses a variable-centered approach, meaning that it investigates the relationship between motivation constructs and academic outcomes rather than how those constructs relate within an individual. Alternatively, person-centered approaches view the person as an integrated whole and, thus, the whole person is the unit of study, not the variable. Methodologically, this means the patterns of psychological constructs within each person are the unit of study (Bergman, Magnusson, & El-Khouri, 2003). Person-centered statistical models, including latent class analysis and latent transition analysis, have the advantage of better representing the theorized constructs as dynamic and interacting factors that affect each other over time within each person. Additionally, by finding the extant patterns of constructs in a sample, they can reveal blind spots in the data where specific combinations do not occur, which can be just as valuable as understanding the combinations that do occur (Bergman et al., 2003).

A few studies have begun to take a person-centered approach to understanding achievement motivation (e.g., Andersen, 2013; Andersen & Chen, 2016; Andersen & Cross, 2014; Archambault, Eccles, & Vida, 2010; Conley, 2012; Musu-Gillette, Wigfield, Harring, & Eccles, 2015; Phelan, Ing, Nylund-Gibson, & Brown, 2017). This line of research asks if there are patterns of within-person motivation constructs that are found across many people. If such groups or classes of people exist, then we can start to understand how people with particular constellations of motivation indicators are different from other groups with different constellations. This type of approach can determine if there are indeed “motivated” and “unmotivated” students and if there are, perhaps, more than just these two categories.

This study investigates if there are discernable motivation categories in a sample of science students in grades four and five in the Baltimore City Public School System (BCPSS) using the expectancy-value-cost motivation framework. If such categories do exist, the study also seeks to better understand the categories, which students are in them, if students transition from category to category over time, and how being in a particular category bears on the future academic achievement of the students. BCPSS is an especially important site for such research because the district serves a population of students that is predominantly African American and living in poverty, two groups that are often underrepresented in science and in motivation research.

This dissertation is comprised of three studies, each using data from the same sample of students. A literature review providing a background pertinent to all three studies is provided. Then each study will be presented with additional literature important for that study, a description of the proposed method, results, and a discussion of the results in light of the extant literature. Finally, a discussion of the three studies will include the implications of the three studies taken as a whole, the limitations of the studies, and suggestions for further research. The three studies will answer the following research questions:

Study 1 Latent Science Expectancy-Value-Cost Motivation Classes:

RQ 1.1) Can science-specific expectancy-value-cost motivation classes be identified in fifth grade science students? What within- and across- class patterns will be observed?

RQ 1.2) How are student characteristics (e.g. race/ethnicity, gender) and education status (e.g., individualized education plan status, English language learner status) related to class membership?

Study 2 Regression of Science Achievement on Latent Science Motivation Classes:

RQ 2.1) How do prior 5th grade science grades predict subsequent expectancy-value-cost motivation class membership?

RQ 2.2) How do the expectancy-value-cost motivation classes described in Study 1 predict future science achievement?

Study 3 Latent Transitions in Science Motivation Statuses:

RQ 3.1) How is class membership in fourth grade related to class membership in fifth grade? What is the likelihood of changing between any two categories from one year to the next?

RQ 3.2) How are transitions between statuses different across student characteristics and educational status?

General Literature Review

The Expectancy-Value Theory of motivation is a comprehensive framework for understanding achievement motivation that is widely used to understand student performance and decisions in a variety of academic subjects and age levels. First developed by Eccles and colleagues (Eccles et al., 1983) to understand achievement and course selection of female high school math students, modern Expectancy-Value Theory of achievement motivation is descendant from earlier work by psychologists primarily studying the behavior of college students in laboratory settings. Over time, Eccles and colleagues have refined the theory, though it remains largely the same as it did in 1983. Since then, several researchers have tested the theory in a variety of academic domains and age groups, and it is consistently shown to be predictive of academic achievement and choices (e.g., Kosovich, Hulleman, Barron, & Getty, 2015; Simpkins et al., 2006; Spinath, Spinath, Harlaar, & Plomin, 2006; Trautwein et al., 2012). Figure 1.1 shows the current configuration of Expectancy-Value Theory as presented in the *Handbook of Child Psychology and Developmental Science, Socioemotional Processes* (Wigfield, 2015, p.659). Important updates to the conceptualization of cost, a facet of Expectanct-Value Theory described below, have brought cost out of task values as its own separate construct (Barron & Hulleman, 2015). This revised framework—expectancy-value-cost motivation, with cost separated from task values—will be used in the studies described below.

Expectancy-value-cost motivation components. Expectancy-Value Theory posits that one's expectancies for success at and values for a particular task are the direct antecedents to the marshaling of energy and effort to begin and persist at a task. Task expectancies are an individual's perceptions of the likelihood that they will successfully complete a particular task. Broadly speaking, subjective task values are individual-specific reasons someone has for wanting to do a task (Barron & Hulleman, 2015; Wigfield, 2015).

As summarized by Wigfield, Tonks, and Klauda, (2016) there are three components of subjective task values—intrinsic, attainment, and utility. A fourth aspect of values, perceived cost, is seen as influencing the extent to which students value a task. Intrinsic value is the enjoyment, if any, an individual will have in attempting and/or performing a specific task. Utility value is the value ascribed to tasks that are perceived to help an individual achieve some goal or carry out a plan. For example, if a college student wants to go to medical school, they might place a high utility value on doing well in organic chemistry, not because they enjoy organic chemistry (though this could also be the case), but because it is a requirement for medical school and thus an important task to succeed at for reaching the goal of attending medical school. Attainment value is the value ascribed to tasks that are important, from the perspective of the student, for a student to do well. Attainment value is tied to identity in that some tasks are highly valued by students because they can, for example, confirm some important aspect of their identity. Perceived costs, which were originally conceived as a fourth aspect of task values (Eccles et al., 1983), are what the individual perceives are the negative aspects of engaging in a task, including the effort needed to complete the task and the loss of opportunity to engage in other tasks.

Reappraisal of perceived costs. Researchers have revisited the concept of perceived cost because, while a component of Eccles and colleagues' original work, this construct has been understudied relative to the other components of subjective task values (Barron & Hulleman, 2015; Flake, Barron, Hulleman, McCoach, & Welsh, 2015). These researchers conceive of cost as a separate component of expectancy-value motivation, presenting instead an expectancy-value-cost framework of achievement motivation (Barron & Hulleman, 2015). In the original formulation of the theory, Eccles et al., (1983) described cost as a moderator of values with three sources – the amount of effort needed to succeed, loss of time available to engage in other valued activities, and the psychological meaning of failure. However, measures of costs of success or failure, the term used by Eccles et al., (1983), were not included in the original study. A measure of the perceived difficulty of doing well in math class, which is likely related to *the effort needed* *to succeed* component of cost, was included, but is theoretically distinct. Furthermore, despite this early conceptualization as a moderator, perceived costs were described as a fourth type of task value in addition to intrinsic value, attainment value, and utility value, in subsequent work (see Flake et al., 2015 for review). The lack of research on and consistent treatment of the perceived costs construct has led to this reappraisal.

Relation to the Proposed Studies. The studies described in chapters two, three, and four utilize a person-centered approach to elementary students' expectancy, values, and perceived costs in science. While there are a few examples of this type of approach in the literature (e.g., Andersen, 2013; Andersen & Chen, 2016; Phelan et al., 2017), the vast majority of research on expectancy-value-cost motivation takes a variable-centered approach. Both approaches are valuable. A variable-centered approach elucidates how the variables relate to each other across individuals and allow researchers to understand general trends at one and several time points. Person-centered approaches, on the other hand, can inform researchers on what patterns occur within individuals and if those patterns are consistent across individuals. For psychological constructs that operate simultaneously within individuals this approach can add valuable understanding to how theoretical constructs operate within individuals while also drawing conclusions about larger groups.

The methods to estimate person-centered models, while not entirely new, are computationally intensive, and so have not been readily available to most researchers until more recently. As a result, there is a lack of person-centered research on expectancy-value-cost motivation. Thus, the proceeding review of literature will rely in large part on the variable-centered research in this area, but will include the available person-centered research to provide the background to motivate the proposed studies (Chapters 2, 3, and 4). When possible, the review will rely on studies of elementary science students. However, elementary science motivation is not as common in the literature as research in other elementary domains (e.g. math and reading) or in science with older students.

Variable-centered research on expectancy-value-cost motivation. As with many psychological constructs, expectancy-value-cost researchers use survey instruments to measure some or all of these constructs (e.g., Conley, 2012; Eccles et al., 1983; Eccles & Wigfield, 1995; Nagengast et al., 2011). In general, these instruments are comprised of Likert-type items that ask students to respond to statements designed to tap into a specific aspect of the theory. The treatment of students' responses to those items has become more sophisticated over time. The earliest research scales were comprised of a set of items designed to measure each construct and psychometric properties of the scales were assessed using Cronbach's alpha (e.g., Sullins, Hernandez, & Fuller, 1995). Subsequent research used exploratory and confirmatory factor analysis to assess the measurement properties of scales being used, but still used the mean of the responses to the items comprising a scale in their descriptive variables and statistical modeling (e.g., Eccles & Wigfield, 1993; Wigfield et al., 1997). These approaches do not account for the error inherent in all measurement. Standard linear regression accounts for error in the outcome, but not in the predictor variables. By including scales with this inherent error unaccounted for as predictors in such models, estimation of coefficients of such scales is less precise and can lead to more type II error.

Motivation researchers now predominantly use latent variable methods, which explicitly model the error inherent in this type of measurement, to both validate the measurement properties of these constructs and model the relations between these constructs and other variables of interest (e.g., Guo et al., 2016; Kosovich et al., 2015; Marsh, Köller, Trautwein, Lüdtke, & Baumert, 2005; Trautwein et al., 2012). These more sophisticated approaches improve precision of predictions because the variation due to random error is removed from the right-side variables in regression and thus associations with left-hand variables are not attenuated due to this error. This increased sophistication in modeling task expectancy, task value, and perceived cost does not prevent the confusion that can arise from the variation in terminology and constructs that has been used in the literature. Understanding the variation in how these constructs have been measured is helpful to understand the literature.

Measurement of expectancy. Measures of expectancies for success on a task should theoretically attempt to measure an individual's perception of the likelihood that they will successfully complete the focal task, which is often success in a specific class at school. However, measures of the related constructs of self-efficacy and self-concept in a specific domain are often used instead. In the model put forth in Eccles et al., (1983) task expectancy is directly influenced by task difficulty and self-concept of ability. In this formulation, one's perception of one's own abilities and one's perception of the difficulty of the task being considered are used to determine the expectancy of success. In the studies presented in that chapter and in subsequent work (e.g., Eccles & Wigfield, 1995), there was little empirical distinction between expectancy and self-concept of ability. As a result, many researchers since have utilized measures of self-concept of ability or self-efficacy instead of task expectancies while situating the work in the context of expectancy-value motivation theory. The impact, if any, of this ambiguity is unclear. In the research reviewed here, items tapping both constructs appear to behave similarly.

Unlike task expectancies, subjective task values are multifaceted by definition (i.e., attainment value, intrinsic value, and utility value), which does not account for recent efforts to further define subcomponents of utility value and attainment value (e.g., Gaspard et al., 2015). There is a great variety of constructs that can be labeled as task values, which requires care in reporting measures and in interpreting results about task values. In some studies all four aspects of task values proposed by Eccles et al. (1983), intrinsic value, attainment value, utility value, and cost, are included (e.g., Conley, 2012). However, many studies utilize a subset of the task values components as a measure of task values. For example Chow and Salmela-Aro (2011) included measures of importance (general task value), usefulness (utility), and interest (intrinsic) values in their study of motivation profiles in several domains, while Nagengast et al., (2011) included only a measure of interest (intrinsic) value in their study of the interaction of task expectancy and task value in predicting engagement in science and science career intentions. There is evidence that, while they are related, the types of task value do separate as distinct factors (e.g., Conley, 2012; Trautwein et al., 2012) and differentially function in predicting achievement and choice (e.g., Guo et al., 2016; Simpkins, Davis-Kean, & Eccles, 2006; Trautwein et al., 2012). The most frequent omissions from the literature are measures of perceived cost.

This variation in task value constructs used is understandable with considerations of survey length, age of students, content domain, and purpose of the study taken into account. For example, Oppermann, Brunner, Eccles, and Anders (2018) included only interest value in the development of a measure of science values for preschoolers for whom other types of values would likely not be relevant. Nonetheless, this variation in included constructs requires care in interpreting and comparing results. Further complicating matters is the recent research to redefine and separate perceived cost as separate from task values (Barron & Hulleman, 2015; Flake et al., 2015).

One aspect of the reappraisal of perceived costs is in regard to definition and measurement of the construct itself. Flake et al., (2015) conducted focus groups with a sample of 121 college students about their most and least motivating classes. While the participating students shared factors related to the “costs of success and failure” identified by Eccles et al., (1983), there were some important distinctions. First, there were two effort-related aspects the students discussed in regards to their least motivating classes. In addition to the already mentioned effort to do well, the effort required in other courses and activities was also mentioned. Flake et al., (2015) proposed a fourth source of perceived costs, outside effort, or the “time, energy or effort, put forth for tasks other than the task of interest.” A second important finding of the qualitative study was that cost appears to be activated when students make a negative assessment of the task. For example, in discussing effort to do a task, a distinction between “a lot of effort” and “too much effort” emerged. Students frequently cited the amount of effort when discussing their most and least motivating classes, but only used language similar to “too much effort” when discussing their least motivating classes. Similarly, students only discussed the loss of time to do other valued tasks when talking about their least motivating classes. So while actual opportunity costs and required effort might be constant in a given situation, a student’s perception of them is not. These results indicate that perceived costs that negatively impact motivation are salient when a there is a negative affective response to the task.

In addition to the evidence provided in Flake et al., (2015), Barron and Hulleman (2015) further support their contention that cost is a third distinct component of achievement motivation rather than a moderator of the effect of values on achievement outcomes. They point to qualitative evidence that children consistently mention cost-related reasons when asked why they do or do not participate in activities in physical education (e.g., Watkinson, Dwyer, & Nielsen, 2005; Xiang, Mcbride, & Bruene, 2006), indicating that perceived costs are salient for children when making decisions about engaging in activities. Quantitative research also indicates that cost is distinct from expectancies and task values. In research that included factor analysis of a perceived cost scale and other expectancy-value-cost motivation measures, the items tapping perceived costs separate into a distinct factor in the best-fitting models (Barron & Hulleman, 2015). In their own work, Barron and Hulleman (2015) found that expectancy is a stronger predictor of achievement while values is a stronger predictor of measures of continued interest. Cost, on the other hand, is a negative predictor of both achievement and continued interest (Barron & Hulleman, 2015). Taken together, these results suggest that cost is a distinct and important construct that operates distinctly from task expectancies and task values.

Flake et al., (2015) proposed that cost is defined as “negative appraisals of what is invested, required or given up to engage in a task” and is comprised of four components—task effort, outside task effort, loss of valued alternatives, and emotional cost. Creation and validation of items to measure these components supported this four-component structure. An important feature of the task effort cost items determined to have good measurement properties was the use of language reflecting that the perceived effort needed to do well on a task was “too much.” Without this language, similar items loaded onto multiple factors. As a result items measuring perceived task effort cost should contain this language.

General findings of expectancy-value-cost research. Despite these inconsistencies in approach, there are consistent findings in regard to how these constructs, variously construed as they have been, operate in general. As discussed above, these results are primarily in a variable-centered framework, but provide an understanding of the macro, sample-level, patterns in which a person-centered approach might reveal heterogeneity. In general, task expectancy and related constructs are positively correlated with task values within a domain. Perceived costs are generally negatively correlated with task expectancies and values within a domain, though there is less evidence available concerning perceived costs. The normative trend is for task expectancy and values to decline over time as students get older. While both task expectancies and values are predictive of academic achievement and choice, task expectancies are generally more predictive of achievement and task values are better predictors of academic choice (Wigfield et al., 2016). Recent work suggests that there is an interaction between task expectancies and task values or between task expectancues and perceived costs in predicting achievement and choice (e.g., Guo et al., 2016; Nagengast et al., 2011; Nagengast, Trautwein, Kelava, & Lüdtke, 2013; Trautwein et al., 2012). When possible, the subsequent sections will detail the research relevant to these claims in elementary science.

Relations between task expectancy, task value, and perceived cost. Whether reported as zero-order correlations of individual items or averages of items, or as correlations of latent factors, a consistent finding in the literature is that elementary students' task expectancy (or a related construct like ability self-perception) and task value(s) are positively correlated. Studies reporting first-order correlations between task expectancy and task values reported correlations ranging from 0.24 to 0.82 (e.g., Chittum & Jones, 2017; Simpkins, Davis-Kean, & Eccles, 2006; Spinath, Spinath, Harlaar, & Plomin, 2006). For example, Chittum and Jones (2017) examined task expectancy, intrinsic value, and utility value for science class in 714 fifth to seventh grade students in two rural schools. Correlations between task expectancy and utility value and between task expectancy and intrinsic value were $r = 0.50$ and $r = 0.59$, respectively. In a validation study of the motivation measures used in the studies described in this proposal and utilizing the subset of the data collected in the 2014-15 school year, a correlation of 0.61 was found between the latent factors representing task expectancy and task value for science class, (Ruzek, McKinney, Grigg, Parker, & Hulleman, in process). Factor analysis of student motivation for science is rare, but similar relationships between latent factors measuring task expectancy and task values in other domains and age groups shows a consistent positive correlation (e.g., Eccles & Wigfield, 1995; Kosovich, Hulleman, Barron, & Getty, 2015).

Domain-specificity of expectancy-value-cost motivation. Across domains, however, the relations between task expectancy, task values, and perceived costs are much weaker. Task expectancy, task value, and perceived cost should theoretically differ across domains because each is determined by a student's perception of their experiences, including past history with that domain, interactions with other people, and their cultural milieu (Wigfield et al., 2016). This theoretical expectation is borne out in the research. Spinath, et. al (2006) measured a task-expectancy-related construct (ability self-perceptions) based on how well students perceived they would do on three United Kingdom National Curriculum activities in each of science, mathematics, and English, as well as intrinsic value (how much students liked science, mathematics, and English) of a sample of 1,678 nine-year-old British children in science, mathematics, and English. In this sample of students, science ability self-perception and science intrinsic value had a correlation of 0.64; in math the same constructs had a correlation of 0.74; and in English the same constructs had a correlation of 0.56. When the researchers related the same constructs across domains (e.g. math self-competence with science intrinsic value) the strength of the relations decreased considerably, ranging from 0.13 to 0.26 for all construct-domain combinations. In other words, having high self-competence in one domain is indicative of having high intrinsic value in that same domain, but that does not translate to other domains. The association of the same construct across domains is similarly weak. In the same study, the correlation of intrinsic value in one domain to intrinsic value in another ranged from 0.22 to 0.32 and the correlation of ability self-perceptions in one domain to those in another ranged from 0.25 to 0.31. In all cases, the across domain correlations are much smaller than those within-domain. These results support the domain-specificity of expectancy-value motivation and point to the importance of measuring and investigating domain-specific motivation.

Domain-specificity is evident in students' mean levels of motivation in different academic domains as well. Eccles and Wigfield (1994) investigated the motivation of 615 first through sixth grade students in math, reading, music, and sports using measures of competence beliefs (how good one believes they are at an activity; a construct related to expectancy), intrinsic value, and utility value in each domain. This longitudinal study followed three cohorts of students for three years. In each year of the study, the mean level of each motivation construct in the sample was different for each domain. Student responses indicated that math and English had the highest mean perceived utility value. In contrast, mean intrinsic value was highest in sports. Heterogeneity in mean task expectancy and task values across domains is consistently observed in studies that assess task expectancy and task value in several domains, including science (e.g., Gaspard et al., 2017; Simpkins et al., 2006).

Relations of perceived costs to task expectancy and task values. As described above, perceived costs are often omitted from expectancy-value-cost research, resulting in a more limited research base from which to understand perceived costs in relation to task expectancy and task values, especially pertaining to elementary science. One recent study (Kosovich et al., 2015) of the science and math motivation of sixth and seventh grade students, examined perceived cost as a distinct factor from task value. These researchers used four cost items reflecting the constructs of perceived task effort, outside task effort, and loss of valued alternatives, but not emotional cost. The four items loaded onto a factor separate from the task expectancy and task value factors in both science and math. Estimated latent correlations indicated that the perceived cost factor was negatively correlated with task expectancy and task values within both science and math (estimated correlations ranged from -0.45 to -056). Ruzek et al., (in process) had similar results in third to fifth grade students' science motivation, reporting latent factor correlations of -0.25 between task expectancy and perceived cost, and -0.20 between task value and perceived cost. These results suggest that for students in science, perceived cost is negatively associated with task expectancy and task value. Based on research using factor analysis in other domains, this appears to be consistent outside of science and math as well (e.g., Gaspard et al., 2017; Guo et al., 2016; Trautwein et al., 2012).

Work presenting zero-order correlations cuts against this conclusion, however. While Conley (2012) and Safavian and Conley (2016) were able to demonstrate the separation of perceived cost into a distinct factor from task expectancy and task values with seventh grade math students, the zero-order correlations of their measure of perceived cost and task expectancy or task value were not as consistently negative as in the examples described above. Both studies use the same survey instrument as each other, which included two perceived cost items measuring loss of valued alternatives. In a study of 1,870 seventh grade math students who predominantly identified as Hispanic (69%) or Asian (17%) in three urban school districts, Conley (2012) reported positive zero-order correlations (latent factor correlations were not reported) of their perceived cost (loss of valued alternatives) with competence beliefs ($r = 0.02$), utility value ($r = 0.11$), interest value ($r = 0.08$), and attainment value ($r = 0.22$) in mathematics, though significance tests were not reported. In a similar but distinct sample of 926 students, Safavian and Conley (2016) reported positive significant correlations between perceived cost (loss of valued alternatives) and utility value ($r = 0.07$) and perceived cost and attainment value ($r = 0.22$). Correlations between perceived cost (loss of valued alternatives) and intrinsic value and perceived cost and efficacy (related to task expectancy) were not significant. These two studies give pause to conclusions that perceived cost is negatively related to task expectancy and task value. However, in these two studies, correlations are based on two survey items tapping the loss of valued alternatives aspect of perceived cost. The studies which report negative correlations measure different types of perceived cost and use factor analysis to account for measurement error. These differences could be a matter of measurement. They could also be indicative of perceived cost functioning differently for different populations of students, as these studies rely on a diverse group of students, including students in elementary school (e.g., Ruzek et al., in process), middle school (e.g., Kosovich et al., 2015), and high school (e.g., Guo et al., 2016); German students (Gaspard et al., 2017); and predominantly non-white American students (e.g., Conley, 2012; Ruzek et al., in process; Safavian & Conley, 2016). Further research on perceived cost in diverse populations is needed.

Association between expectancy-value-cost measures and outcomes. As proposed in Eccles et al.'s original formulation (1983) and future elaborations/iterations of expectancy-value-cost theory (e.g., Barron & Hulleman, 2015; Eccles, 2009; Wigfield & Cambria, 2010; Wigfield et al., 2016) students' task expectancy and task value are predictive of important achievement-related outcomes, including achievement itself, course choices, extracurricular choices, and persistence at a task in primary, secondary, and higher education settings. The academic courses available to elementary students are usually set for students by the school and are compulsory, making course choice less relevant in this context. As a result, I will focus on results from achievement outcomes here. In general, domain-specific task expectancy is predictive of achievement in that domain, with higher levels of expectancy associated with higher levels of achievement. Similarly, higher levels of domain-specific task values are also often associated with higher achievement in that domain (e.g., Eccles et al., 1983; Marsh et al., 2005; Steinmayr & Spinath, 2009). When achievement is regressed on both task expectancy and task values in the same model, the coefficient on task value often does not continue to be a significant predictor of achievement (Trautwein et al., 2012).

In elementary science, specifically, the studies examining the relation between expectancy-value-cost motivation and achievement (e.g., science class grades, standardized test results) is limited, but is in line the broader expectancy-value-cost motivation literature. Spinath et al. (2006) found correlations between teacher-determined grades in science, math, and English and domain-specific measures of ability self-concept (related to task expectancy) and intrinsic values. Positive significant correlations in all three domains, ranging from 0.11 to 0.40 for ability self-concept and from 0.04 to 0.26 for intrinsic value, were found, although the science domain had the weakest associations. Similarly, Senler and Sungur (2009) reported correlations between science achievement (classroom grades) and each of science self-concept (related to task expectancy) and task values (measured by intrinsic and utility values) in a sample of Turkish fourth through eighth grade students. For the elementary students in this sample, the correlation between science self-concept and science grades was 0.58 and the correlation between science task value and science grades was 0.3. These limited results in elementary science students suggest that task expectancy and task value are positively related to achievement outcomes in elementary students as in other domains and age levels.

To my knowledge, there is one study that relates perceived costs of science to science achievement in elementary students (Ruzek et al., in process). That study employrd a subset of the sample used in the studies described in this dissertation (i.e., the data collected in the 2014-15 school year) to validate the expectancy-value-cost measure used in the studies detailed in chapters 2, 3, and 4. In that study three items tapping perceived cost (effort cost and emotional cost) were significantly negatively correlated with achievement on standardized science assessment scores (r from -0.18 to -0.30). Research with older students across several domains indicates a similar relationship between perceived cost and achievement (e.g., Kosovich et al., 2017; Safavian & Conley, 2016; Trautwein et al., 2012). For example, Kosovich et al., (2015) found correlations between achievement in math and science and domain-specific perceived cost of -0.17 to -0.41 in their study of expectancy-value-cost motivation of middle school students. The limited results relating domain-specific perceived cost to achievement encourage further research in this area.

Interactions of expectancy, value, and cost. The early versions of expectancy-value-cost motivation theory were termed "Expectancy X Value" theory (e.g., Atkinson, 1957) to indicate the multiplicative relationship between expectancies and task values in determining a person's motivation for a task. In the translation of this theory for the real-world setting of educational contexts, rather than the controlled laboratory settings for which it was initially developed, this multiplicative interaction was seemingly lost, most likely due to methodological reasons rather than a principled theoretical stance (Nagengast et al., 2011). The ability to model interactions in a latent framework was not available until recently. Additionally, if there is an interaction, it might be small and require larger samples to identify. With new methods in latent models and large samples, a contingent of researchers have investigated the interaction of task expectancy, task values, and perceived costs (e.g., Guo et al., 2016; Nagengast et al., 2011, 2013; Trautwein et al., 2012).

The search for an interaction has been fruitful. As predicted by theory, there does appear to be a multiplicative association between expectancies and task values or expectancies and perceived costs in predicting achievement. For example, Trautwein et al. (2012) examined the math and English self-concept (related to expectancy), attainment value, intrinsic value, utility value, and perceived cost in a sample of 2,508 German students in their final year of secondary school. Measures of these constructs in each domain were used to predict achievement in the form of standardized math and English exams from the Third International Mathematics and Science Study and the Test of English as a Foreign Language, respectively, while controlling for gender, prior achievement, cognitive ability, and school type. In each domain, models with just one of the motivation constructs (e.g. only attainment value) and controls predicting achievement were estimated. The results of these models aligned with other research. Self-concept, values, and reverse-coded costs were each significant and positive predictors of achievement, with the exception of utility value for English. The regression coefficient of self-concept (0.46 in mathematics; 0.54 in English) was the largest when compared to the values and cost constructs (betas ranging from 0.16 to 0.41). When self-concept was paired with one of the values or cost constructs but without an interaction, self-concept remained a significant predictor of achievement in both domains, while task values either became non-significant or the magnitude of the coefficient decreased dramatically (e.g., 0.51 to 0.06 for utility value for English). The authors note this is likely due to the high correlation of self-concept and task values. Finally, models including the interaction indicated in all cases that the interaction of self-concept and one of attainment value, intrinsic value, utility value, and perceived cost (reverse coded) are significant and positive predictors of achievement in both domains.

A similar study of 1,978 German ninth grade math students had slightly different results. Without self-concept in the model, some task value factors (a second-order global task value factor, intrinsic value factor, and cost factor) were positive significant predictors of math achievement while attainment value and utility value were not. When modeled with the self-concept factor as a predictor, the significant results on the different task value factors went away except for cost (reverse coded), which remained a positive significant predictor of math achievement. When latent interactions were modeled, the interaction between the second-order factor of global task value and the self-concept factor as well as the interaction of self-concept and cost (reverse-coded) were both positive significant predictors of math achievement. These results and the results of Trautwein et al. (2012) support the expectancy x values interaction in predicting achievement, albeit in secondary math and English for German students.

Achievement motivation researchers are interested in the academic choices and interests students have in addition to academic achievement. When researchers look at a variety of such outcomes, a positive significant interaction is found as well. In the study of ninth grade math students by Nagengast et al., (2011), there were positive significant interaction terms of self-concept and global task values in predicting student self-reported effort and teacher-reported student engagement in mathematics. A significant interaction has also been found in studies examining engagement in homework (Nagengast et al., 2013), participation in extracurricular science activities (Nagengast et al., 2011), and science career aspirations (Nagengast et al., 2011). These studies each involved a different set of constructs (e.g., using self-concept vs. expectancy and/or a subset of attainment value, utility value, intrinsic value, and perceived costs). These results further support the concept that energy toward a variety of achievement-related tasks is highest when task expectancies of success (and expectancy-related beliefs like self-concept) and task values are both high. While all of the studies that included a measure of perceived cost include it as a type of task value, there is also evidence of an interaction between task expectancy and perceived cost.

None of the studies probing for an interaction between expectancy and task values described above models the interactions of the multiple task values and perceived costs with each other in addition to with expectancy, though these interactions are certainly discussed in theory in the literature. The authors indicate that care should be taken in interpreting the results, since combinations of extreme values that one could use to calculate predicted outcomes from results might not actually exist in the data. Despite these warnings, there is minimal indication of the extent to which different combinations of expectancies, task values, and perceived costs actually exist among the students that comprise the samples. An alternative approach would be to first ask what combinations of levels of expectancies, task values, and perceived costs exist in the students in a sample and then ask how those different combinations might relate to important academic outcomes. This can be achieved with person-centered methods like latent class analysis and latent transition analysis, which I use in the studies described herein.

Person-centered research on expectancy-value-cost motivation. Person-centered research views the individual as an integrated whole and, as a result, takes the individual as the unit of study. The development of an individual is complex and dynamic and involves their own agency and interactions with their environment. To model this perspective, methods like latent class analysis are used to find the patterns of constructs of interest within the individual, rather than how variables relate across individuals. The results of person-centered research in expectancy-value-cost motivation, while limited, has provided new insights into how the theoretical constructs typically included in variable-centered research relate to each other within students (Andersen, 2013; Andersen & Chen, 2016; Conley, 2012; Viljaranta, 2010; Viljaranta, Nurmi, Aunola, & Salmela-Aro, 2009), and on the heterogeneity of trajectories of change in levels of motivation over time (e.g., Archambault, Eccles, & Vida, 2010; Kosovich, Flake, & Hulleman, 2017). These approaches also have the value of reflecting the social-cognitive nature of motivation theories like expectancy-value-cost theory. As described above, a student's motivation is a result of their experiences, past and present, filtered through their perception of those experiences. This includes interactions with other people (especially parents and teachers), past achievement experiences, personal and collective identity, and cultural milieu (Eccles, 2009). These social influences are experienced by the individual and the perceptions of those experiences reside solely in their brains. For a given task in a given context, each individual has their own level of task expectancy, task values, and perceived costs, which are posited by this theory to then determine that individual's actions or lack thereof. Because person-centered approaches like latent class analysis look for patterns within individuals, they are better suited to model this aspect of social-cognitive theories like expectancy-value-cost motivation. A more detailed review of person-centered research on expectancy-value-cost motivation is provided in *Chapter 2 – Study 1*.

The studies described in the following chapters use latent class analysis and latent transition analysis to understand the heterogeneity of patterns of expectancy-value-cost science motivation in a sample of fourth and fifth grade students. In Study 1, latent class analysis is used to determine if there are discernable patterns of expectancy-value-cost science motivation in this sample of students and to describe those patterns. Study 2 examines the association between the latent classes and prior and subsequent academic achievement in the form of science class grades and standardized science assessment scores. Study 3 uses latent transition analysis to understand how students transition from one latent status (class) to another between fourth and fifth grades. Differences in class membership and transitions between important student subgroups will be examined as well. This research will add to the growing body of person-centered research on expectancy-value-cost motivation and will shed light on the interrelation of task expectancy, task values, and perceived costs both within students and over time and how they relate to achievement.

Figures

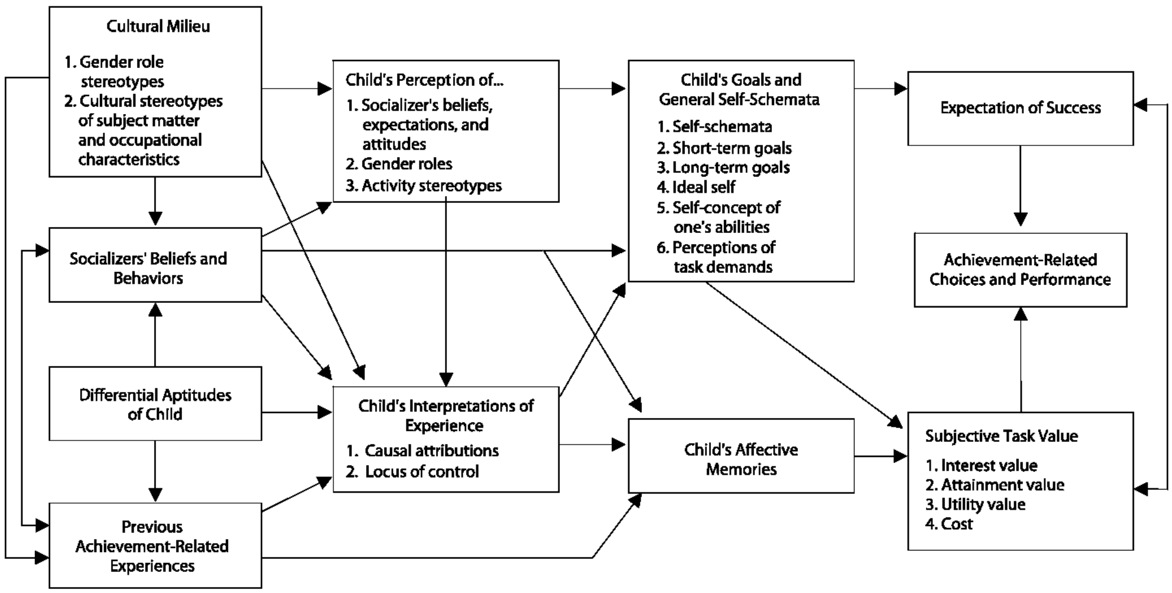


Figure 1.1 The Eccles et al., Expectancy-Value model of achievement motivation. From "Development of achievement motivation and engagement" by Wigfield, A. (2015). Handbook of Child Psychology and Developmental Science, Socioemotional Processes, 657.

Chapter 2—Study 1: Latent Science Motivation Classes

Much attention and energy has been directed toward the improvement of science education in the United States over the past several decades (e.g., American Association for the Advancement of the Sciences, 1993; Change the Equation, 2014; National Academy of Sciences, 2006; National Research Council, 2012; Obama, 2011). The concern is focused on increasing academic achievement in K – 12 science as well as advanced course-taking both for the purposes of increasing the number of students pursuing science degrees and for progressing toward the goal of science literacy for all. Achievement motivation has shown to be effective in predicting student achievement, persistence, and choice in several academic domains, including science (e.g., Chamorro-Premuzic, Harlaar, Greven, & Plomin, 2010; Eccles et al., 1983; Lu, Weber, Spinath, & Shi, 2011; Senler & Sungur, 2009; Simpkins, Davis-Kean, & Eccles, 2006). Additionally, research on interventions targeting motivation indicates that student motivation is both malleable and, when positively affected within a student, results in increased achievement and course-taking (Guthrie, McRae, & Lutz Klauda, 2007; Harackiewicz et al., 2012; Hulleman et al., 2017; Lazowski & Hulleman, 2016; Rozek, Svoboda, Harackiewicz, Hulleman, & Hyde, 2017). Thus motivation in science is a potential avenue through which to affect change in student achievement, persistence, and choice in science.

For interventions to be as effective as possible for each student, understanding motivation in students is key. The expectancy-value-cost theory of motivation (Barron & Hulleman, 2015; Eccles et al., 1983; Wigfield et al., 2016) is a comprehensive socio-cognitive theory of achievement motivation which has proven useful in describing student motivation and predicting achievement behaviors. This theoretical framework, brought to relevance in education by Eccles and colleagues (Eccles et al., 1983), posits two constructs—*expectancies for success* and *subjective task values*—that are the psychological antecedents to putting energy towards completing and persisting at a task. Expectancies for success are an individual's subjective assessment of their likelihood of completing a task at an acceptable level to themselves and answer the question "Can I do this?" Subjective task values are the individual's subjective reasons for doing a task and answer the question "Do I want to do this?" (Barron & Hulleman, 2015; Eccles et al., 1983). Both of these constructs are theoretically and empirically influential on student achievement, persistence, and academic choices, and are influenced by student perceptions, past experiences, identity, and interactions with other social actors (Eccles et al., 1983; Wigfield et al., 2016). This study aims to better understand the expectancy-value-cost science motivation of a sample of Black/African-American elementary students in a large urban school district.

Expectancy-Value-Cost Motivation

Expectancies for success are most immediately influenced by a student's task-specific self-concept and perceptions of task difficulty. These are, in turn, influenced by students' perceptions of past events (e.g. performance on similar tasks); important socializers' (e.g. parents and teachers) behavior, expectations of students, and perceptions of student competence; and cultural milieu (Eccles et al., 1983). Essentially, for each task, students evaluate their perceptions of their abilities for that task, as well as how difficult they think that task will be, and make a determination of the likelihood that they will satisfactorily complete that task. Perceiving that one might do well, however, is not enough to motivate one to put effort into the task; one must also value that task in some way.

The value that an individual places on a task can take many forms. Expectancy-Value Theory provides three main types of value to organize the reasons for doing a task—intrinsic value, utility value, and attainment value. Intrinsic value is reflective of the pleasure one receives from engaging in a task. Utility value reflects the ways in which a task helps to accomplish something not directly related to the process of the task itself. So, for example, a student who takes organic chemistry in order to meet prerequisites to attend medical school has utility value for organic chemistry. Attainment value is related to the ways in which engagement in and completion of a task helps to confirm a salient aspect of an individual's identity. This could include, for example, a student engaging in a task that they perceive will show they are athletic and a desire on the part of that student to appear athletic. For every task, an individual assesses the ways in which they value an activity and in conjunction with their task expectancy for success make a decision to put effort into and persist at a task.

Eccles et al.'s original formulation of the Expectancy-Value Theory of achievement motivation also described perceived costs of engaging in a task. In this original formulation, costs were theorized as having a moderating effect on the influence of values on achievement and choice. In the time since that research was published, a large amount of attention has been paid to task expectancy (and related constructs) and task values. Perceived costs, on the other hand, are not as consistently covered in motivation research. In recent years, several researchers have begun to reappraise the cost construct shedding light on the properties of this aspect of motivation (Barron & Hulleman, 2015; Flake et al., 2015). In the reframed expectancy-value-cost motivation framework, Barron and Hulleman (2015) provide evidence that perceived cost plays a unique role separate from task expectancies and task values and should be considered a third component of Expectancy-Value Theory, rather than as a sub-component and moderator of task values. In this revised expectancy-value-cost framework, perceived costs answer the question "Am I free of barriers preventing me from investing time, energy, and resources into the activity?" Four components help to answer this question—task effort, outside effort, loss of valued alternatives, and emotional cost. *Task effort* is the perception of the effort required to complete the task under consideration. *Outside effort* is the perception of the effort needed to complete other tasks. *Loss of valued alternatives* is the perception of what other valued tasks and the concomitant rewards/results one has to give up to engage in the task being considered. *Emotional cost* is the negative affective response associated with engaging in the task (Flake et al., 2015). Studies measuring perceived cost in a manner reflective of this reappraisal suggest that cost is a separate construct, loading onto factors separate from task expectancy and task value, and is negatively associated with both task values and task expectancies (Conley, 2012; Flake et al., 2015; Kosovich et al., 2015; Ruzek et al., in process). For ease of description "expectancy-value-cost motivation" will be used from here on to encompass research in this new formulation as well as prior research in which perceived costs were considered a subcomponent of task values.

Relations of elementary science expectancy, value, and cost. The expectancy-value-cost framework has proven useful in understanding the motivation of students across many domains, especially math and reading (e.g. Archambault et al., 2010; Baker & Wigfield, 1999; Eccles et al., 1989, 1983; Eccles & Wigfield, 1995), though there is representation of foreign language, sports, music, and science in the literature (e.g., Andersen & Chen, 2016; Chiang et al., 2011; Eccles & Wigfield, 1995; Gaspard et al., 2017). While these constructs are theoretically (Wigfield et al., 2016) and empirically (e.g., Eccles & Wigfield, 1995; Gaspard et al., 2017; Trautwein et al., 2012) domain-specific, there are within-domain patterns of association between task expectancy, task values, and perceived cost that are consistent across domains. Task expectancy (and related self-efficacy and self-concept) and subjective task values are found to be positively correlated (e.g., Conley, 2012; Eccles & Wigfield, 1995; Kosovich et al., 2017; Ruzek et al., in process; Safavian & Conley, 2016; Trautwein et al., 2012). When measures of more than one type of task value are included and reported separately, each is positively correlated with the others (e.g., Gaspard et al., 2017; Guo et al., 2016; Trautwein et al., 2012). Measures of cost, though less frequently included in studies, especially the more recent formulation of perceived costs, are negatively associated with expectancies and values (e.g., Flake et al., 2015; Kosovich et al., 2017; Ruzek et al., in process), though some zero-order correlations are less consistently negative and significant (e.g., Conley, 2012; Safavian & Conley, 2016). Correlations are useful for understanding how these variables relate to each other in a sample of students, but tell researchers less about how these constructs relate to each other within an individual. If we are to understand how motivation operates within an individual, we must begin to describe intra- rather than inter-individual relations of expectancy-value-cost motivation.

Person-Centered approach. The expectancy-value-cost framework is a useful way to understand motivation because it describes the cognitive factors that result in directed action toward a task and how those factors are connected to each other. Because these factors are cognitive, they are not immediately observable. A popular method for understanding expectancy-value-cost measures is confirmatory factor analysis (CFA), which accounts for the unobservable nature of these constructs by modeling a latent variable that represents the construct(s) of interest and the error inherent in measuring such constructs. Structural equation models are frequently used to relate how the modeled factors relate, on average, to predictors and outcomes of interest. These are variable-centered approaches, which model how the mean levels of the motivation constructs are related to each other within a sample. Less commonly, motivation researchers have taken a person-centered approach to expectancy-value-cost motivation, asking if there are consistent patterns of how these constructs relate to each other within a student.

A person-centered approach can build upon the knowledge gained from variable-centered approaches, and have gained popularity in motivation research (e.g., Andersen, 2013; Chen, 2012; Chow & Salmela-Aro, 2011; Conley, 2012; Murdock & Miller, 2003; Phelan et al., 2017; Roeser & Peck, 2003; Viljaranta, 2010; Viljaranta et al., 2009). Person-centered approaches take the individual as the unit of study and ask what the pattern of variables is within an individual, and if there are any patterns that are consistent across larger groups of people (Bergman et al., 2003). These methods better reflect the fact that social cognitive constructs, such as task expectancy, task value, and perceived cost, are theorized to reside within the individual and are a result of the whole of that individual's experience. Modeling a linear relationship between covariates, outcomes, and each social cognitive construct belies this aspect of these constructs. A consistent finding of variable-centered work is that the expectancy and value constructs are positively correlated within a sample (Eccles et al., 1983; Eccles & Wigfield, 1995; Kosovich et al., 2015; Lu et al., 2011; Senler & Sungur, 2009; Simpkins et al., 2006). Person-centered approaches can help understand if there are typical patterns of expectancy and values that lead to that correlation. For example, are all students either high on expectancy and value or low on expectancy and value? Are there students for whom expectancy and value are at odds (one high and one low)? Answers to these questions can contribute to our understanding of how these constructs operate within individuals.

Person-centered studies of expectancy-value-cost measures. While the application of person-centered methods to motivation has increased in the last twenty years, there are only a handful of studies that include expectancy-value-cost related constructs. There are none, to my knowledge, that focus on elementary science students. Nonetheless, it is instructive to understand the findings of similar research to inform the current study. In his dissertation, Smith (2017) used cluster analysis to identify reading and motivation for reading profiles in 187 third through fifth graders in three North Carolina schools. The reading motivation clusters were identified from student responses to the Motivation for Reading Questionnaire (MRQ, Wigfield & Guthrie, 1995), which includes measures of motivation constructs related to expectancy (self-efficacy), general task values (importance), intrinsic value (curiosity, involvement), and utility value (recognition, grades). Six clusters were identified—a high cluster in which students reported high levels in all measures, a low cluster in which student reported low levels in all measures, two clusters of unique combinations of high and average levels of each construct, and two clusters with unique mixtures of high and low motivation constructs. In some sense the clusters reflected general high, medium, and low levels of motivation for reading, but different clusters were distinguished from others by different aspects of motivation for reading, supporting the hypothesis that there are qualitative differences in reading motivation between elementary students. Similar results were found by Baker and Wigfield (1999) using the MRQ with a sample of 371 fifth and sixth graders. The MRQ used in these studies was built from a few motivation theories and, as a result, most of the measures used are related to expectancy-value-cost motivation, but were not developed to directly measure expectancy, values, or cost. Research with older students has included measures of expectancy-value-cost motivation.

Conley (2012) used cluster analysis with measures of expectancy-value-cost and achievement goal theory constructs specific to math on a sample of 1,870 seventh grade students in 40 middle schools in Southern California. Cluster analysis was performed on student responses to questions tapping achievement goals and expectancy-value-cost-related constructs – subjective task values (interest, utility, and attainment), perceived cost (loss of valued alternatives), and competence beliefs (related to expectancies)—in math. Results indicated a seven-cluster solution. Focusing on the relation of self-competence, task values, and perceived costs in each cluster reveals that if the seven clusters are ranked by their mean level of self-competence, the result is also very nearly a ranking on the means of each of interest value, attainment value, and utility value. While the means of student responses are different for each of these sub-constructs, they appear to track together when viewed this way. When viewing cost in the same manner, however, the ranking of mean cost within each cluster results in a very different order from the other expectancy-value-cost constructs. These results align with the correlational results found in this study and others, indicating that expectancy and expectancy-related constructs are coupled with subjective task values within an individual, whereas perceived cost does not track as tightly.

Similar results were found by Roeser and Peck (2003). While they used general academic motivation, rather than a domain-specific measure, they found six clusters of measures of perceived academic competence, perceived academic value, and emotional distress (a measure of general anger and depression moods) in a sample of about 1,500 seventh grade students in Maryland. In all but one cluster, academic competence and value tracked together. Emotional distress, as with perceived cost in the Conley (2012) study, did not track as closely with the two other constructs. Importantly, the three clusters with highest levels of distress had the lowest seventh and eight grade grade point averages and the lowest achievement on a seventh grade standardized math test, despite one such cluster having higher perceived academic competence and value than a cluster with lower academic distress. These results indicate that cost (and related constructs) may be a distinguishing and salient aspect of student motivation profiles.

Barron and Hulleman (2015) suggested that cost has both a moderating effect, as originally described by Eccles and colleagues (Eccles et al., 1983), and an effect independent of expectancies and task values. If this is the case, then cost being the differentiating factor between these clusters has implications for how one might approach assessing student motivation and implementing targeted interventions.

Person-centered research on profiles of task values across domains (e.g., Chow & Salmela-Aro, 2011; Viljaranta et al., 2009) and variable-centered research on expectancies, task values, and perceived costs (e.g., Denissen, Zarrett, & Eccles, 2007; Eccles & Wigfield, 1995; Gaspard, Häfner, Parrisius, Trautwein, & Nagengast, 2017; Kosovich et al., 2015; Wigfield, Eccles, Mac Iver, Reuman, & Midgley, 1991) indicate that expectancy-value-cost motivation is domain-specific. While the current study centers on elementary science students, to my knowledge, the only science-specific person-centered studies of expectancy-value-cost motivation (Andersen, 2013; Andersen & Chen, 2016; Andersen & Cross, 2014; Phelan et al., 2017) use the nationally-representative sample of ninth grade students from the first year of data of the High School Longitudinal Study (HSLS-09, Ingels et al., 2011) or a sample of eighth grade students in the case of Phelan et al.. The HSLS data used by Andersen and colleagues include the following motivation measures in each of science and math domains: self-efficacy, interest value, attainment value, and utility value. Separate latent profile analyses for math and science self-efficacy, interest value, attainment value, and utility value each resulted in the choice of four-profile solutions (Andersen & Cross, 2014). The four profiles in each domain were remarkably similar, consisting of a low profile, an average profile, and two high profiles differentiated by higher self-efficacy in one and higher utility value in the other.

The study by Phelan et al. (2017) also excluded a measure of perceived cost, but did include four items measuring science expectancy and self-concept, and four items measuring task values (utility, general importance, intrinsic). Survey responses from two cohorts of students, totaling 509 students, were analyzed using latent class analysis. Results for both cohorts indicated similar three-class solutions, which the researchers labeled “Science is me,” “Indifference,” and “Science is not me,” reflecting a similar high, moderate, and low level of motivation found in the studies described above. In both cohorts, the “Science is not me” latent class was estimated to comprise about half of the sample, while the “Science is me” class comprised less than ten percent of the sample.

The extant person-centered research on expectancy-value-cost science motivation is limited to this one group of studies, but aligns with similar research in other domains and age levels as described above. Taken together, these results suggest that a similar approach to elementary science profiles could be similarly fruitful in uncovering qualitatively different constellations of motivation constructs that will contribute to our understanding of how these constructs relate to each other within an individual. This type of approach better reflects the Expectancy-Value Theory, which posits that it is expectancy, value, and cost that determine an individual’s behavior. The limited research that includes measures of perceived cost indicate that this construct may be particularly salient in differentiating categories of student motivation.

Purpose of the Current Study

This study aims to add to the growing body of person-centered expectancy-value-cost motivation research. To date, this research has largely excluded elementary science students and has generally excluded measures of perceived cost. This study will address this gap in the literature by examining latent expectancy-value-cost motivation in a sample of fifth grade science students. Specifically, this study will address the following research questions:

1) Can science-specific expectancy-value-cost motivation classes be identified in elementary science students in fifth grade?

2) What within- and across- class patterns can be observed?
3) How are student characteristics (e.g., race/ethnicity, gender, IEP status, ELL status) related to class membership?

Method

The sample utilized in this study is a part of a National-Science-Foundation funded Math Science Partnership grant that aims to improve STEM education in nine elementary schools through a partnership between the Baltimore City Public School System (BCPSS) and Johns Hopkins University. The project also recruited five schools to serve as comparison schools, for a total of 14 schools involved in the project. As a part of the grant, a student survey was administered in the participating project and comparison schools in the spring of each school year. The motivation data presented in this study were collected in the participating schools in the spring of the 2014-15, 2015-16, and 2016-17 school years.

Sample. Student surveys were administered by trained researchers and research assistants. Through an agreement with the school district, consent to survey all third through fifth grade students in the participating schools was granted. Students were able to opt out of any of the surveys or other data collection activities at any time. While some students refused to participate, this was rare. Over the course of the three school years that this study spanned, 1,489 fifth grade students were surveyed. Student IDs from the district were used to link students to their demographic information from the school district. Some student observations were not matched to their district ID and as a result were not included in the analysis, resulting in a loss of 9.2% of observations. Additionally, due to an inability to establish measurement invariance in latent classes across certain groups (detailed below) only students identified as Black/African American and who were neither Latinx nor English Language Learners (ELLs) were included in this study. As a result, the analytic sample consists of 860 students. Table 2.1 shows student gender/sex, race/ethnicity, free-and-reduced-price-lunch eligibility, English language learner (ELL) status, and individualized education plan (IEP) status of students in the full sample and the analytic sample.

Measure of expectancy-value-cost motivation. Six items of the student survey (Table 2.2), tapping into the task expectancy, task value, or perceived cost motivation constructs, were used in this study. For each item, students were presented with a gradient of five answer choices that ranged from, for example, “not at all sure” to “completely sure.” Student responses were recoded as 0 if they responded with either of the first two response options (e.g., “not at all sure,” or “a little bit sure”), 1 if they responded with any of the last three response options (e.g. “sure”, “very sure”, or “completely sure”), and “NA” indicating missing data.

Student information. Demographic information was obtained from district administrative records. Ideally, students would directly provide how they identify themselves in these areas. That, however, was not a part of the student survey, so the race/ethnicity, and sex/gender recorded by the school district will be used. A student’s IEP status was obtained from district administrative data, and coded as 1 if the student was identified as having an IEP and 0 if not. A student’s status as an English language learner was also obtained from district administrative data, and coded as 1 if the student was identified as an English language learner and 0 if not.

Latent Class Analysis. Latent class analysis (LCA) was used to identify classes of science expectancy-value-cost motivation using student survey responses. Models with one to eight classes were estimated using the software MPLUS v7.4 (Muthén & Muthén, 2012) for the six items described above. The TYPE = COMPLEX setting of the ANALYSIS command was used to adjust standard errors to account for the clustering of students in classrooms. The bootstrapped likelihood ratio test (BLRT) and lower Bayesian Information Criteria (BIC) were used for model selection, which simulations by Nylund, Asparouhov, and Muthén (2007) showed were best at uncovering the correct number of latent classes. The BLRT tests a model with k classes against a model with $k-1$ classes. A non-significant result indicates that the model with one more class does not significantly improve fit over the $k-1$ class model. The k class model for which the BLRT is significant and the BLRT for the $k+1$ model is not is considered favorable.

Measurement Invariance. Given the historical underrepresentation of women and people of color in science and more recent efforts to increase the participation of these underrepresented groups (Change the Equation, 2012), it is important to understand if there are differences in motivation class between subgroups. Students who have been identified as having disabilities and/or as being English language learners are underrepresented in expectancy-value-cost motivation research. This study includes a designation for these groups of students to build upon that limited knowledge.

Measurement invariance across these subgroups was be assessed in two steps for each grouping variable (race/ethnicity, gender, ELL, IEP). First, the number of latent classes in each subgroup was determined using the same procedure as for the entire sample. If the number of classes in each subgroup was the same as the whole sample, then a constrained and an unconstrained model were each estimated. In the constrained model, the item response probabilities were constrained to be equal in each subgroup, and in the unconstrained model they were allowed to differ between subgroups. Because these models are nested, a χ^2 difference test based on the difference in *-2*loglikelihood* for each model was used to test the hypothesis that the unconstrained model fit the data better than the constrained model.

Results

Student responses to the six survey items are shown in Table 2.2 in their raw form (response options one to five). The percent of responses that were coded as 1 when the variable was dichotomized is indicated in parentheses. As is evident, students were much more likely, on average, to endorse the higher levels of the task expectancy (89%), general task value (91%), intrinsic value (87%), and utility value (85%) items than for the effort cost (30%) and emotional cost (23%) items.

Number of classes and measurement invariance. The BLRT and BIC indicated that a three-class model fit the data best (Table 2.3). Tests of measurement invariance indicated that, in some cases, unconstrained models in which item response probabilities were allowed to differ across groups provided statistically significantly better fit than a model in which those probabilities were constrained when considering groupings. As a result, only students identified as Black, not Latinx and non-ELL (n = 860) were retained for the remainder of the analysis. Measurement invariance tests were non-significant for male/female and IEP/non-IEP groupings, indicating that the meaning of the latent classes is the same for these grouping and thus comparing class membership across groups has a meaningful interpretation.

Latent classes. A profile plot of the three-class model using the final analytic sample is shown in Figure 2.1. Estimated class prevalences are indicated in the legend. The y-axis represents the estimated item response probabilities for the six dichotomized items included in the analysis. The most prevalent latent class, representing an estimated 73% of the sample, was labeled *High Expectancy and Value (High EV)* and is highly likely to have responded with higher science task expectancy (96.5%) and science task values (> 94%) with a low probability of indicating higher perceived cost for science (< 19%). These probabilities are higher, in the case of task expectancies and task values, and lower, in the perceived costs, than the sample prevalence of these items (see Table 2.2).

The second-most prevalent class (17%), the *Low Expectancy, High Cost (Conflicted)* class, is distinguished by predicted probabilities for task expectancy (71%) that are lower than the sample average (89%) and predicted probabilities for perceived costs (81%, 65%) that are higher than the sample average (30%, 23%). The predicted probabilities of endorsing the higher values of the task value items (95%, 80%, 79%) were on par with the sample averages for the same items (91%, 72%, 85%). The especially high likelihood (95%) of endorsing the higher values of the general task value item ("How important is science to you?") is similar to the *High EV* class described above. This latent class is labeled *Conflicted* because they have average task values, indicating they have reasons to do science, but have lower task expectancies to do well in science and perceive higher costs than their peers in their science class, presenting a conflict in their motivational state.

The members of the least prevalent group (10%), labeled *Low Expectancy and Value, Moderate Emotional Cost (Low EV)*, have a somewhat low probability of endorsing the higher levels of the task expectancy item (62%), and a low probability (< 38%) of endorsing the higher levels of the task value and perceived cost items. These estimated item response probabilities for the task expectancy and task values items are lower than the sample proportions for those items (85% - 91%), especially the task value items. The item response probability for the effort cost item (29%) was about the same as the sample proportion (30%) while the item response probability for the emotional cost item (36%) was higher than the sample proportion (23%).

Latent class regression. The three latent classes were regressed on gender (female = 1) and IEP status. Results indicated that there was no statistically significant relationship between being female and latent class membership ($p > 0.05$). There was a statistically significant relationship ($p < 0.001$) between a student having an IEP and latent class membership in the *Conflicted* class relative to the *High EV* class. Specifically, students with an IEP had 4.3 times the odds of being in the *Conflicted* class and not the *High EV* class as compared to their peers without an IEP. In terms of predicted probabilities, 40% of students with an IEP were predicted to be in the *Conflicted* class while only 13% of students without IEPs were predicted to be in the *Conflicted* class. Having an IEP was not predictive of being in the *Low EV* class relative to the other latent classes.

Discussion

Latent class analysis revealed three classes of distinct constellations of task expectancy, task value, and perceived costs in science for a sample of Black/African American fifth graders in an urban school district. Rather than a multitude of combinations of these constructs, three qualitatively distinct classes emerged from the data, which would otherwise be obscured by whole sample statistics. The *High EV* class was most likely to endorse higher levels of task expectancies and task values and lower levels of perceived costs. The *Conflicted* class was more likely than not to endorse higher levels of task expectancies and task values and had the highest likelihood of endorsing higher levels of perceived cost; however the likelihood of endorsing higher values of task expectancies was lower than the sample average. The *Low EV* class had a relatively lower likelihood of endorsing task expectancies and task values and had relatively low likelihood of endorsing higher levels of perceived cost, though not as low as the *High EV* class.

That the *High EV* class, which, on its face, is the most adaptive of the three classes, was the most prevalent class, representing an estimated 73% of the sample, is encouraging. This is in contrast to latent class analyses with older science students which found much lower prevalences of the most adaptive latent classes (Andersen & Cross, 2014; Phelan et al., 2017). The samples and measures in each of these studies are quite different, so it is unclear how to interpret these differences. Nonetheless, the remaining 27% of students in this sample are estimated to be in either the *Conflicted* class (17%), which perceives costs to school science, or the *Low EV* class (10%), which does not particularly value science. The two classes indicate qualitatively different and potentially maladaptive motivation towards science that could be addressed with different motivation interventions.

These findings and past person-centered expectancy-value-cost motivation research (e.g., Andersen, 2013; Andersen & Chen, 2016; Andersen & Cross, 2014; Baker & Wigfield, 1999; Conley, 2012; Phelan et al., 2017; Roeser & Peck, 2003; Smith, 2017) support the notion that expectancy-value-cost motivation constructs are related to each other within individuals in limited and particular ways. Across these studies, patterns in the relationship of task expectancies and task values emerge, while the limited research including perceived costs can only suggest a consistent set of patterns across students.

Task expectancies and task values. The extant person-centered expectancy-value-cost motivation literature, including the current study, has uncovered classes (or clusters) of motivation constructs in which task expectancies (and related constructs like self-efficacy) and task values generally track together, meaning that students in classes with higher levels of task expectancy also generally have higher levels of task values. When examining the results of the current study, for example, the three classes represent a rank ordering of both task expectancies and task values, from *High EV* with the highest levels of both, to *Conflicted*, and finally to *Low EV*, with the lowest levels of both. Phelan et al., (2017) found similar results with different but related survey items in a sample of eighth grade physical science students. This pattern is generally true in the other studies mentioned above, with some small exceptions. These exceptions, however, are small differences and the general rule that within a class or cluster higher levels of task expectancies are associated with higher levels of task values holds across these studies, which include students of different ages and in different content areas.

These results are also consistent with variable-centered expectancy-value-cost literature which generally finds that within a domain task expectancies and task values are positively correlated (e.g., Eccles et al., 1983; Eccles & Wigfield, 1995; Kosovich et al., 2015; Lu et al., 2011; Senler & Sungur, 2009; Simpkins et al., 2006). The macro pattern that within samples these two constructs are generally positively associated is revealed as a result of the two constructs being closely associated within each individual with, for example, a “high expectancy, low value” individual being a rare case. These results should inform interpretations of research examining the interaction of task expectancies and task values (e.g., Guo et al., 2016; Nagengast et al., 2011; Nagengast, Trautwein, Kelava, & Lüdtke, 2013; Trautwein et al., 2012). While it is mathematically possible, using results of such studies to estimate outcomes of such high-expectancy-low-value individuals, this within-person pattern might be infrequent in actuality, rendering such estimations less informative for educators, policy-makers, and researchers alike. However, the studies examining such interactions are based on different samples from the studies using latent class and cluster analysis, and the extent to which the patterns of task expectancies and task values generalize across all samples is unknown. More person-centered research on different samples should be conducted to determine if this pattern continues to hold across diverse samples and content areas.

Perceived cost in relation to task expectancies and task values. Within the three classes that emerged in this study, levels of perceived cost did not align with levels of task expectancies and task values. Instead perceived cost served as the clearest distinction between the *Conflicted* class and the *High EV* class, which both had higher likelihoods of endorsing higher levels of task expectancy and task values. And while the *Low EV* class exhibited a relatively low likelihood of perceiving costs, the predicted probability of endorsing the higher levels of the emotional cost item was substantially higher than for the *High EV* class. This can be interpreted as students in this class perceiving costs in the form of stress in science class, rather than not having enough time to do well in science class. This may be because these students, as indicated by their responses to the task expectancy and task values items, are less likely to perceive that they can do well in science class and to value science and thus are less concerned with doing well in science class, but are still able to be stressed out by science class.

Person-centered studies of expectancy-value-cost motivation that include measures of perceived cost are quite limited. Conley (2012) found that perceived cost, in the form of loss of valued alternatives, was important in distinguishing among several clusters of math motivation measures, especially clusters with similar levels of math self-competence and math task values. While this result is similar it involves a measure of a different aspect of perceived costs than in the current study. These results suggest that perceived costs may indeed play an important role in distinguishing types of expectancy-value-cost motivation, though further research is needed to build on these studies.

The within-class relation of perceived costs to task expectancies and task values observed in this study also provide insight into correlational results of variable-centered research. Perceived costs are usually negatively correlated with task expectancies and task values but with lower magnitude correlations than task expectancies and task values have to each other. This macro pattern is manifest in the most prevalent *High EV* class where students endorse higher levels of task expectancy and task values, and lower levels of perceived cost. However, in the other classes, perceived cost aligns more with task expectancy and task value, attenuating the negative correlation.

Recent attention to the role of perceived costs has suggested that perceived costs be brought out of the umbrella of task values as a distinct construct that also influences and is influenced by task expectancies and task values (Barron & Hulleman, 2015). While these results represent a snapshot of motivation at a single point in time and cannot speak to the influence of each construct on the others over time, these results do support the assertion that perceived costs are distinct from task expectancies and task values. Perceived costs are neither completely aligned with task expectancies and values nor are they the inverse of these constructs. The results described above further suggest that perceived costs are salient when task values are present within a student with lower task expectancy. Perceived costs were highest in the *Conflicted* class, which exhibited levels of task values similar to the *High EV* class and levels of task expectancy similar to the *Low EV* class. The causal ordering of these relationships is not possible in this study, but these findings add complexity to our understanding of intra-individual expectancy-value-cost motivation. While more research with different samples and diverse measures is needed to confirm these findings, these results suggest that perceived costs are most prevalent when task expectancies are relatively low, when task values are relatively high, and, as discussed below, for students with IEPs.

Student subgroups. Tests of measurement invariance between important subgroups in the initial sample indicated that latent class models allowing different item response probabilities for students of differing race/ethnicity (i.e., Black/African-American and Latinx) and for English language learner status provided statistically significantly better fit than a model in which item response probabilities were constrained to be equal. Analyses in this study focused on the largest subgroup for which measurement invariance was confirmed—Black/African-American students who were not identified by the school district as either Latinx nor as an English language learner.

Given the historic underrepresentation of Black/African-American individuals in STEM fields and the emphasis on STEM education for such underrepresented groups (Change the Equation, 2012), it is encouraging that a large majority (73%) of this sample of fifth grade students were estimated to be in the *High EV* class. The potentially less adaptive *Conflicted* and *Low EV* classes provide a starting point for teachers, parents, and other stakeholders to understand different students' motivation and to devise potential interventions to address each student's motivation. It is also encouraging, given the historic underrepresentation of females in STEM fields, that there was no difference in class membership based on a student's identified gender in this sample. Phelan et al., (2017) similarly find no difference in class membership between genders in their study of eighth grade science students.

In contrast to gender, students in this sample who were identified as having an IEP were estimated to have significantly higher odds of being in the *Conflicted* class relative to the *High EV* class. These students perceived science to be important, useful, and enjoyable, and have a lower probability of thinking they can do well in science compared to their peers, but also perceive that they are stressed out in science class and do not have the time to do well in their science class. That such a maladaptive latent class was found and is so tightly related to a student having an IEP is alarming. Teachers are often encouraged to modify assignments for students with IEPs. These results suggest that, students in this class, whether they have an IEP or not, might be benefit from accommodations and interventions designed to reduce these perceived costs in science class rather than interventions targeted at task expectancies or task values.

Tables

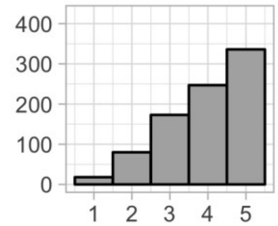
Table 2.1 *Sample Size, Student Sex/Gender, Race/Ethnicity, Free Lunch Eligibility, and Educational Status of Full and Analytic Samples*

	Full Sample *n* = 1364 *n* (%)	Analytic Sample *n* = 860 *n* (%)
Female	698 (51.2)	450 (52.3)
Black	882 (64.7)	860 (100)
White, Latinx	399 (29.3)	—
White, non-Latinx	65 (6.8)	—
Asian	19 (1.4)	—
American Indian, Pacific Islander, multiple race	25 (1.8)	—
Free- and reduced- price lunch eligibility	1119 (82.0)	776 (90.2)
Students with an individualized education plan (IEP)	164 (12.0)	124 (14.4)
English language learners (ELL)	200 (14.7)	—

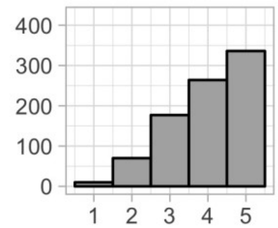
Table 2.2 *Expectancy, Value, and Cost Survey Items Wording and Student Responses*

Item Wording (% of responses coded as 1[b]) | **Student Responses[a]**

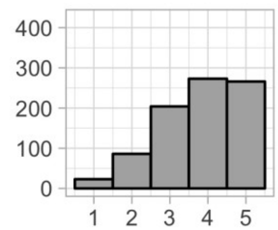
Task Expectancy
How sure are you that you can learn science this year?
(89%)



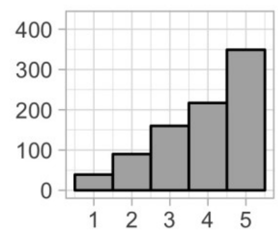
Task Value Item 1, Importance
How important is science to you?
(91%)



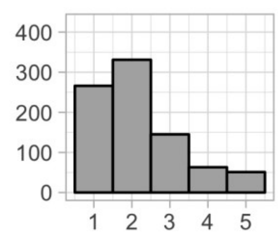
Task Value Item 2, Utility
How useful is science to you?
(87%)



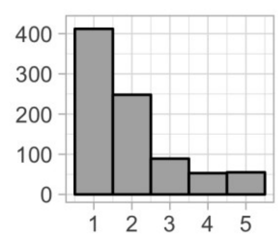
Task Value Item 3, Intrinsic
Overall, how interested are you in learning about science?
(85%)



Perceived Cost Item 1, Effort
How difficult is it to find the time to do well in your science class?
(30%)



Perceived Cost Item 2, Emotional
How stressed out are you by your science class?
(23%)



Note: [a] Student survey responses were initally coded as, e.g., "Not at all sure" = 1, "A little bit sure" = 2, "Sure" = 3, "Very sure" = 4, and "Completely sure" = 5. [b] For analysis, values of 1 or 2 were coded as 0, and 3, 4, or 5 as 1.

Table 2.3 *Fit Indices and Bootstrapped Likelihood Ratio Test Results for Different Latent Class Models*

Number of Classes	Number of Parameters	Log-likelihood	AIC	BIC	SABIC	Entropy	BLRT p-value
1	6	-2245.504	4503.008	4531.549	4512.495		
2	13	-2101.577	4229.154	4290.994	4249.71	0.706	0
3	20	-2069.069	4178.139	4273.278	4209.763	0.722	0
4	27	-2061.072	4176.143	4304.58	4218.836	0.881	0.08
5	34	-2053.291	4174.581	4336.317	4228.342	0.878	0.13
6	41	-2050.305	4182.61	4377.644	4247.439	0.823	0.94
7	48	-2047.82	4191.64	4419.973	4267.538	0.792	0.9
8	55	-2045.465	4200.931	4462.562	4287.897	0.833	0.87

Note: AIC = Aikake information criteria; BIC = Bayesian information criteria, SABIC = sample-size-adjusted BIC; BLRT = bootstrapped likelihood ratio test

Figures

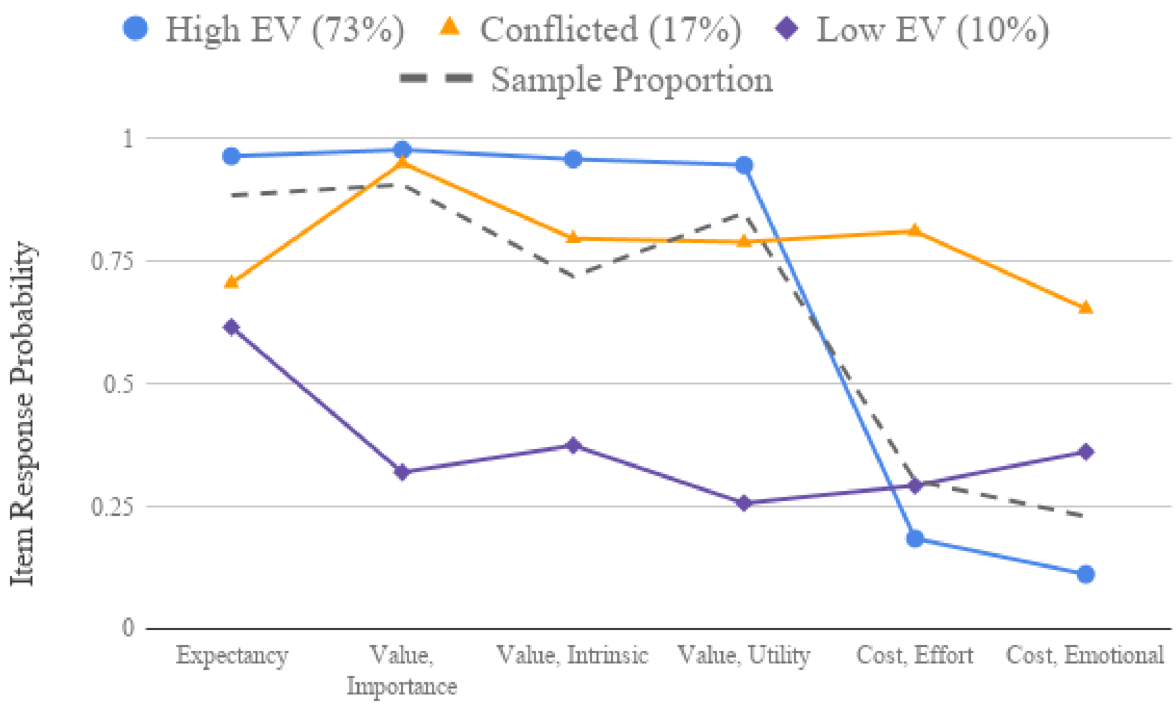


Figure 2.1. Profile plots of three latent expectancy-value-cost science motivation classes, class prevalences, and sample proportions of item responses.
Note: E = Expectancy, V = Value

Chapter 3—Study 2: Latent Classes and their Relation to Academic Achievement

The latent classes identified in study 1 shed light on the categories of intra-individual relations between the task expectancy, task value, and perceived cost constructs and how gender and special education status are associated with class membership. The current study asks how membership in those classes is associated with student science achievement in the form of science classroom grades and state standardized science assessments. The results of this study will have both practical and theoretical consequences. Practically, this study will indicate which latent class or classes are predictive of higher levels of future achievement (i.e. are “adaptive”) and should be encouraged, and which latent class or classes is/are predictive of lower levels of achievement (i.e., are “maladaptive”), and should raise concern. This information could then be translated into a guide for educators using similar motivation surveys. Theoretically, this study can shed light on how the expectancy, value, and cost constructs, taken together as they occur in a sample of students, are related to important academic outcomes. This chapter presents the research questions associated with this study, relevant literature not discussed above, hypotheses, and the proposed method for answering the research questions.

Research Questions

RQ 2.1) How do prior 5th grade science grades predict subsequent expectancy-value-cost motivation class membership?

RQ 2.2) How do the expectancy-value-cost motivation classes described in Study 1 predict future science achievement?

Literature Review

Research using the expectancy-value-cost framework of achievement motivation (Barron & Hulleman, 2015; Eccles et al., 1983; Wigfield et al., 2016) has consistently shown that academic achievement is related to measures of task expectancy (and related constructs), task values, and, when included in studies, perceived cost (e.g., Chamorro-Premuzic et al., 2010; Conley, 2012; Eccles et al., 1983; Kosovich et al., 2015; Senler & Sungur, 2009; Simpkins et al., 2006, 2006; Spinath et al., 2006; Trautwein et al., 2012; Viljaranta, 2010), including some evidence of reciprocal influences over time (e.g., Marsh et al., 2005; Simpkins et al., 2006). The United States has seen a multiple-decades-long push for improved science achievement to foster greater scientific literacy and an increased in the number of individuals entering science and science-related careers (American Association for the Advancement of the Sciences, 1993; Change the Equation, 2014; Haag & Megowan, 2015; National Academy of Sciences, 2006; National Research Council, 2012; Obama, 2011). Given this reciprocal relation, student expectancy-value-cost motivation is a promising leverage point for improving science course-taking and achievement in the service of these science education policy goals. Because elementary students usually have little choice in their core academic classes it is most salient and practical to focus on achievement outcomes, like classroom grades and standardized test scores, rather than course selection. For this reason, the current study relates the expectancy-value-cost motivation of fifth grade science students to their achievement in science. Thus, the subsequent sections will focus on the extant evidence of the relation of expectancy-value-cost motivation to achievement. When available, research on students in elementary grades and/or science class will be highlighted.

Relation of expectancy-value-cost motivation to achievement. The general finding that within-domain achievement and expectancy-value-cost motivation are correlated extends to achievement both prior and subsequent to the time when the measure of motivation was administered. In some cases, the time-ordering of the measures is explicit and purposeful (e.g., Marsh et al., 2005; Simpkins et al., 2006), while in others it is a matter of practicality. Despite the differences in time-ordering there are consistently positive correlations of task expectancies and task values with achievement and consistently negative, though with less evidence, correlations of perceived costs and achievement. Nonetheless, the theoretical reasons for the association between expectancy-value-cost motivation and either prior or subsequent motivation are distinct and will be described separately.

Relation of prior achievement to subsequent expectancy-value-cost motivation. Theory posits that prior achievement experiences, including receiving grades in a course or scores on standardized assessments, are filtered through a student's interpretation of those events. This interpretation involves a student's assessment of the locus of control for that achievement. For example, if a student receives a poor grade but perceives that this was outside of their control (say because they were out of class for two weeks and had trouble catching up when they came back) they are less likely to internalize this event as an indication of their abilities. As a result this event might not impact their future task expectancies for grades in the same and similar classes. Whereas if a student perceives that they put in a great deal of effort to get a good grade, but did not receive such a high mark, this event might have a greater impact on their self-perception of ability which would, in turn, influence their subsequent task expectancy in similar situations. This is one theorized pathway for prior achievement to impact subsequent motivation though, in reality, it is far more complex and includes influences from peers, parents, and teachers about the achievement event, a student's goals and values, and any number of other personal and contextual factors. Despite the complexity of the potential pathway from prior achievement to changes in subsequent motivation, several studies have shown that prior achievement predicts subsequent task expectancy (and related constructs), task values, and perceived costs (e.g., Chamorro-Premuzic et al., 2010; Eccles et al., 1983; Kosovich et al., 2015;

Simpkins et al., 2006; Viljaranta, 2010). The theorized connection to subsequent achievement is less complex.

Relation of expectancy-value-cost motivation to subsequent achievement. An individual's task expectancy, task values, and perceived costs for a particular task, while informed by their current and prior experiences, are the constructs that directly lead to putting effort towards a task, which, frequently, results in success at that task. This is borne out in the numerous of studies that have shown that prior task expectancy, task values, and perceived cost are predictive of subsequent achievement (e.g, Chamorro-Premuzic et al., 2010; Conley, 2012; Eccles et al., 1983; Ruzek et al., in process; Senler & Sungur, 2009; Simpkins et al., 2006; Trautwein et al., 2012; Wang, Chow, Degol, & Eccles, 2017).

It is generally accepted that expectancies are more predictive of achievement than subjective task values (e.g., Wigfield et al., 2016). Each construct is often predictive of achievement when modeled as a predictor of achievement in separate regression models (e.g., Guo et al., 2016; Trautwein et al., 2012). When task expectancies and task values are modeled at the same time, coefficients on task values often become non-significant (e.g., Guo et al., 2016; Ruzek et al., in process). The theory supports these findings as well. If you value a there is no guarantee that you are good at that task. People, on the other hand, are good judges of their ability and thus their task expectancy is a good indicator of whether or not they will do well on that task. Expectancy and value are also correlated—people tend to value things they are good at and are good at things they value—which brings issues of collinearity in regression to bear. This has led researchers to model the interaction of expectancies and values.

Interaction of task expectancy and task values. A group of researchers has brought attention to the interaction of expectancy and value in predicting academic outcomes in research on this particular theory. They point out that the Expectancy X Value Theory described by Atkinson (1957), which Eccles and colleagues adapted for an educational setting (1983), was based on the idea, and which was empirically supported by controlled laboratory experiments, that in order for one's motivation to act to be highest both expectancy and value needed to be high. In other words, neither thinking you could do well on a task (expectancy) nor thinking a task was important (task value) was sufficient—you need to both think you are good at something and want to do it. According to personal correspondence with Eccles, as cited by Nagengast et al., (2011), the interaction present in early versions of this theory was absent from the theory put forth by Eccles and colleagues because they did not find any interaction when they ran their models and thus focused instead on the relationships that were present, leaving the question of an interaction for further investigation. Nagengast and colleagues have revisited this topic in several studies utilizing latent interaction structural equation models. This is an important improvement over linear regression models with interaction terms of manifest variables because these models account for the measurement error inherent in the types of measures used to measure motivation constructs. This group of researchers has also taken advantage of large national and international data sets, leveraging the statistical power of their large samples to find interactions, which are likely to be small, if present. Using this approach, these researchers found significant interaction coefficients (Guo et al., 2016; Nagengast et al., 2011, 2013; Trautwein et al., 2012) providing support for the multiplicative effect of expectancy and value on academic achievement and choice.

This approach to assessing the impact of the interaction of expectancy and values is limited, however. For example, aside from the work by Guo and colleagues, task values is either modeled as a general task values construct (e.g., Nagengast et al., 2013) in the investigated domain or in separate models each with an interaction between expectancy and one type of value (e.g., Trautwein et al., 2012). Theoretically each type of value and perceived costs all interact with each other and task expectancy to result in an individual's motivation and subsequent actions. Modeling all of those interactions in this manner would quickly become quite complex. Furthermore, results estimating the combined effect of different combinations of each construct can be misleading. For example, Nagengast et al., (2011) present a graph of predicted achievement over continuous values of expectancy for five levels of values—average, +/- 1 SD of values, and +/-2 SD of values—to illustrate to the reader the potential multiplicative effect of the interaction. What is not addressed in their presentation is just how common different combinations of expectancy and values are in the sample. As the authors point out, interpreting over the full range of each variable without understanding how frequently, say, high expectancy and low values occur can lead to extrapolation from the data.

Person-centered analysis of expectancy-value-cost. An alternative to this approach would be to first ask what patterns of task expectancy, task value, and perceived cost exist in a sample of students and then investigate if these particular patterns are differentially associated with achievement and other important outcomes. Researchers have already shown that meaningful patterns of expectancy-value-cost motivation constructs can be identified on their own and in conjunction with other motivation constructs (e.g., Baker & Wigfield, 1999; Chen, 2012; Chow, Eccles, & Salmela-Aro, 2012; Chow & Salmela-Aro, 2011; Conley, 2012; Linnenbrink-Garcia et al., 2018; Perez et al., 2019; Phelan et al., 2017). Identifying such patterns has the advantage of finding particular student profiles that teachers and other educational professionals can use to identify students in need of intervention, reinforcement, and/or encouragement (Phelan et al., 2017), especially when these patterns can be associated with important outcomes.

There is limited person-centered research on science expectancy-value-cost motivation classes or categories. Most of the existing examples involve samples of middle, high school, and college students (e.g., Andersen, 2013; Andersen & Chen, 2016; Andersen & Cross, 2014; Linnenbrink-Garcia et al., 2018; Perez et al., 2019; Phelan et al., 2017) though one includes elementary students (Linnenbrink-Garcia et al., 2018). This research indicates that categories or classes of science motivation can be uncovered.

Furthermore, there are consistent patterns in the categories and classes described in each study. In all of these studies, some measure of task expectancy (or a related construct) and task values was included. In general, within a category or class, the task expectancy and task values tracked together, meaning that within a class or category both task expectancy and task values were at similar levels relative to the levels in other classes or categories. For example, Phelan et al., (2017) administered a survey with four items tapping science class task expectancy and science self-efficacy and four items tapping task values, including intrinsic value and attainment value, to two samples of eighth graders, totaling 509 students, in the fall and spring of the same school year. Each item had four answer choices, ranging from strongly disagree to strongly agree. For the purposes of analysis, student responses were recoded 1 for strongly agree and 0 for all other responses for each item. Latent class analysis revealed similar three-class solutions in both samples—the "Science is me" class (estimated 9% of both samples) included students with a high probability of strongly agreeing with all eight items; the "Indifference" class included students who had a moderate probability of strongly agreeing with all of the items, and the "Science is not me" class had a low probability of endorsing strongly agree for all eight items.

Andersen and colleagues (Andersen, 2013; Andersen & Chen, 2016; Andersen & Cross, 2014) identified similar high, moderate, and low classes of both math and science expectancy-value motivation. They, however, had a four-class solution, with two high categories, "high science/math self-efficacy" and "high science/math utility value," which, as their labels imply, are differentiated by having higher levels of self-efficacy and utility value, respectively. Despite these differences, both studies show that these methods can reveal important aspects of the heterogeneity in samples. In this case, these classes are consistent with the high positive correlation between task expectancy and task values. Importantly, neither study found a profile that combined a relatively high level of task expectancy with a relatively low level of task values or vice-versa. Lacking from these studies is a measure of perceived cost, which would provide useful evidence for understanding the role perceived cost plays in student science motivation.

When perceived cost was included in a similar study of math motivation (Conley, 2012), perceived cost was important in differentiating between classes. Conley (2012) surveyed 1,870 seventh grade students who identified predominantly as Asian and Hispanic in 40 middle schools in Southern California. Cluster analysis resulted in a seven-cluster solution of scales measuring achievement goals (mastery goals, performance-approach goals, and performance-avoidance goals), subjective task values (interest, utility, and attainment), perceived cost (loss of valued alternatives), and competence beliefs (related to expectancies) in math. It is not surprising that the addition of new measures (achievement goals and perceived cost) resulted in more clusters than the research described above. Interestingly, the patterns of self-competence and task values in this study are similar to those found by Phelan et al. and Andersen and colleagues (Andersen, 2013; Andersen & Chen, 2016; Andersen & Cross, 2014; Phelan et al., 2017) in that task-expectancy-related measures and task value constructs tracked with each other within each cluster. In other words, if the seven clusters are ranked by their level of self-competence, the result is also very nearly in rank order of the clusters' respective levels of interest value, attainment value, and utility value. The level of perceived cost in the form of loss of valued alternatives, however, did not track in the same way—the ranking of clusters by mean level of perceived cost is very different from that of any of self-efficacy and the task values measures. In this study, perceived cost was negatively correlated with self-efficacy and task values measures, but the magnitude of this correlation was not as large as the correlation between self-efficacy and task values. These results reveal the underlying heterogeneity in individual motivation patterns that manifests in sample-level correlations and point to perceived cost as an important distinction between clusters with similar levels of self-efficacy and task values.

How these expectancy-value-cost motivation classes relate to achievement and other outcomes is interesting from a theoretical and practical perspective. Focusing on expectancy-value-cost motivation in science, Phelan et al., (2017) found that students in the "Science is me" class had higher mean levels of science interest, measured by students interest in: studying science after high school, having a career involving science, and taking science courses in the future. Andersen (2013) found that clusters with higher levels of self-efficacy and task values had higher average math achievement test scores (a measure of science achievement was not available in the data set utilized). These results indicate that the intra-individual patterns revealed in person-centered motivation research have predictive power for important educational outcomes, which encourages further research into the ability of science motivation classes to predict important educational outcomes. Additionally, to my knowledge there are no studies in which prior achievement is related to expectancy-value-cost motivation classes, profiles, or clusters.

Present study. Study 2 builds on the literature described above and the results of study 1 of this dissertation. As described in study 1, three latent expectancy-value-cost science motivation classes were uncovered (Figure 3.1) in this sample. A brief description of each latent class follows (see study 1 for a full description of method and results). The estimated item response probability profile of the most prevalent latent class, *High Expectancy and Value* (*High* EV, 73%)*,* was distinguished by higher-than-sample-average probability of responding with higher levels of the task expectancy item and all three task value items, and lower-than-average probability of responding with higher levels of both perceived cost items. The item response probability profile of the *Low Expectancy, High Cost* class (*Conflicted,* 17%) was distinguished by the highest estimated probability of responses indicating higher levels of perceived cost and with lower-than-average estimated probability of endorsing higher task expectancy. The third class, *Low Expectancy and Value (Low EV* 10%), was distinguished by the lowest estimated probabilities of endorsing higher levels of task expectancy and all three task value items. The present study investigates the relation of these latent classes to one measure of prior science achievement—5th grade quarters 1 & 2 science grade—and three measures of subsequent science achievement—5th grade quarter 4 science grade, 6th grade science grade, and 5th grade state standardized science assessment score.

Hypotheses

Research question 2.1 asks, "How do prior fifth grade science grades predict subsequent expectancy-value-cost motivation class membership?" I hypothesized that higher grades would be most associated with increased odds of being in the *High* EV class relative to both the *Low EV* class and the Conflicted class. I did not make a hypothesis about the change in log odds for students receiving higher grades for the *Conflicted* class relative to the *Low EV* class. Variable-centered research helped inform the hypotheses for this research question because of the lack of person-centered research relating prior achievement to expectancy-value-cost motivation classes.

When researchers relate prior achievement to subsequent task expectancies (and related constructs), task values, and perceived costs, higher achievement is associated with higher levels of task expectancies and task values, and with lower levels of perceived costs. In a study of middle school students using similar motivation measures, Kosovich et al. (2015) found that for both science and math, task expectancy and task values were positively correlated, and perceived costs were negatively correlated, with achievement on standardized assessments in each subject. These results are consistent with studies that relate task expectancies (or related constructs) and task values to prior achievement (e.g., Chamorro-Premuzic et al., 2010; Eccles et al., 1983; Simpkins et al., 2006). These results lead me to hypothesize that higher prior achievement would be predictive of being in the *High EV* class rather than either the *Low EV* class or the *Conflicted* class. The *High EV* class has higher levels of task expectancy and task values, and lower levels of perceived cost, which are all predicted by higher achievement.

Hypotheses regarding how achievement will predict being in the *Low EV* class relative to the *Conflicted* class is less clear. These two classes exhibit about equal probability of higher levels of task expectancy and are differentiated by higher levels of task values and perceived cost in the *Conflicted* class compared to the *Low EV* class. Prior low achievement is theorized and observed to predict lower levels of task expectancy, suggesting that there may be no difference in how prior achievement predicts membership in these classes relative to each other. However, lower achievement is also theorized to lower task values and increase perceived costs. Empirically, however, when controlling for prior motivation, the link between prior achievement and task values is not as consistently observed as with task expectancy (e.g., Simpkins et al., 2006; Viljaranta, 2010). The limited number of studies that include perceived costs limits how prior literature can inform hypotheses for this study. Theoretically, prior negative experiences, including negatively-interpreted lower grades, could be internalized by the student as increased perceived costs for future similar tasks. The balance between which of these constructs is most influenced by prior achievement is unclear and so I did not make a hypothesis regarding the relation between prior grades and the odds of being in the *Low EV* class relative to the *Conflicted* class.

Research questions 2.2 and 2.3 ask how class membership predicts subsequent science achievement in the form of classroom grades and standardized assessment scores, respectively. I hypothesized that membership in the *High EV* class would be predictive of the highest achievement, followed by the *Low EV* class, and then the *Conflicted* class. Theory and empirical work on the interaction of task expectancy and task values would imply that, ignoring perceived cost, the *High EV* class would be most predictive of higher subsequent achievement, the *Low EV* class would be predictive of lower subsequent achievement, and the *Conflicted* class would predict achievement between the other two. However, the *Conflicted* class has much higher levels of perceived cost than the other two classes. Perceived cost has been shown to be negatively predictive of subsequent achievement, including in a similar sample as in the current study (Ruzek et al., in process) and, in a study of the interaction of self-concept and task values (with perceived costs conceptualized as a facet of task values), perceived cost was the only task value facet that had a significant regression coefficient and interaction above and beyond the influence of a general task values factor in predicting achievement (Guo et al., 2016).
As a result, I hypothesized that membership in the *Conflicted* class will predict, on average, lower grades than membership in the *Low EV* class.

Method

The particpants in this study are the same 860 students in study 1. The analysis here builds on the latent class analysis performed in study 1 which used survey data collected in the third quarter of the school year in 14 elementary schools in Baltimore City. The latent classes described in study 1 will be related to student achievement in the form of science class grades and state standardized science assessment scores.

Science grades. The grades students received in science class in fifth and sixth grade were obtained, when available, from district administrative data. In this district, teachers report student grades in each quarter of the school year. In fifth grade, grades are reported to students as letter grades of "E- Excellent", "G - Good", "S -Satisfactory", "P - Poor", or "U – Unsatisfactory," which have the rough equivalent meaning of the more traditional letter grades of "A," "B," "C," "D," and "F," respectively. For the purposes of this analysis, the grades were recoded to the numerical values of 95, 85, 75, 65, and 55, respectively (these are the middle-value of the district reported ranges for each letter grade, e.g., 70-79 for an "S"). To capture the achievement in science class in the first half of the school year, before the survey was administered, the science grades from the first two quarters of the school year were averaged. If a grade from one quarter was missing, the other grade was used as the average. If grades from both quarters were missing, the fifth grade quarter 1 and 2 science grade was coded as missing. This resulted in 851 students with a value for fifth grade quarter 1 and 2 science grade. The final quarter science grade, which occurred after survey administration, was used to capture fifth grade science achievement after the administration of the survey. The fifth grade quarter 4 science grade was present for 824 students. In contrast to fifth grade, students receive whole a number percent as a grade in middle school (e.g., 97%, 63%, etc.) ranging from 50% to 100%.

For sixth grade, grades for all four quarters were averaged together to capture science achievement in sixth grade. In the case of missing data, averages were calculated for the available quarters' grades when possible. Sixth grade science grades were available for 765 students.

Fifth grade state science assessment. The Maryland School Assessment (MSA) in science was administered to fifth graders in the spring of 2015 and 2016. In 2017, the state piloted a new Next-Generation-Science-Standards-aligned science assessment and will not make the results of that assessment available. As a result, science assessment data was only available for two of the three cohorts of students in the data and was obtained for 582 students. The MSA science was designed to assess students' knowledge and skills relative to the Maryland State Curriculum, which indicate what students should know and be able to do based on the Maryland State Science standards. Each form of the test is scaled using item response theory (IRT) to a common scale, theta. The theta is then scaled to an operational scale that is more easily interpretable by students, teachers, and parents. As a result the scale scores for MSA science range from 240 to 650 with a target mean of 400 and a standard deviation of 40. The reliability of the 5^{th} grade scale score is (*stratified* $\alpha = 0.92$, Pearson/MSDE, 2012).

Relation between latent classes and achievement. To answer research question 2.1, the R3STEP option of the AUXILIARY command in Mplus v.7.4 (Muthén & Muthén, 2012) was used to regress latent classes on prior achievement. Figure 3.2a shows an idealized representatin of this model. This method uses a three step procedure to estimate how a change in the predictor variable (prior grades in this study) is associated with a change in log odds of membership in latent class relative to another latent class. To answer research question 2.2, the automatic BCH option of the AUXILIARY command in Mplus v.7.4 (Muthén & Muthén, 2012) was used to estimate mean subsequent achievement for each latent class. Figure 3.2b shows an idealized representatin of this model. While not shown, these analyses were also conducted with a series of restricted samples to ensure that differences in results were not a result of differential missingness across the achievement measures. For each pair of outcomes, a restricted sample was created by dropping all observations with misssing data on either achievement measure. An additional restricted sample which dropped all observations that were missing any of the four achievement measures was also created. The substantive interpretation of the resuls, reported below, were the same with all subsamples. Results reflecting the largest possible sample for each achievement measure are presented below.

Results

The sample in study 2 is the same sample used in study 1. The sample consisted of 860 fifth grade students all of whom were identified as Black/African-American. About half of the students were identified as female (52%). A large majority of students (90%) were eligible for the federal free- and reduced-price meal program. About one in seven (14%) of students were identified as having an IEP.

Student achievement. Intercorrellations among the dichotomized survey items and the achievement measures as well as the mean and standard deviation of each are summarized in Table 3.1. The distribution of science grades and science assessment scores are shown in bar charts and histograms in Figure 3.3. The mean fifth grade quarter 1 and 2 science grade that students received was 77.46 (*SD* = 10.39). The distribution of fifth grade quarter 1 and 2 science grades is shown in figure 3.3a. The most common average first half grade was 75% (Satisfactory, *n* = 166), followed by 85% (Good, *n* = 141), and 80% (Good/Satisfactory, *n* = 132), indicating that the plurality of students received grades in the middle of the grading scale. Many fewer students received the lowest grades possible (55%, Unsatisfactory, n = 38; 60% Unsatisfactory/Poor, n = 40) and the highest grade possible (95%, Excellent, n = 59). Nine students did not have grade data in the first half of fifth grade.

The mean fifth grade quarter 4 science grade that students received was 79.13 (SD = 11.63). The distribution of fifth grade quarter 4 science grades is shown in figure 3.3b. The most frequent fourth quarter grade was 85% (Good, n = 250) followed by 75% (Satisfactory, n = 234). The least frequent grade was 55% (Poor, n = 74). For fourth quarter science grades, 73 students were not matched to a grade in the administrative data.

The mean fifth grade state standardized science assessment score was 356.54 (SD = 41.90). The distribution of fifth state science assessment scores is shown in figure 3.3c. The distribution of scores is unimodal and ranges from 240 to 474, though relatively few students score in the lowest and highest regions of the distribution.

In sixth grade, students receive grades that are whole number percents, ranging from 40 to 100. As a result, when averaged over four quarters, these grades can take on many distinct values. The mean sixth grade science grade students received was 74.86 (SD = 11.05). The distribution of sixth grade science grades is shown in Figure 3.3d. Sixth grade science grades have a bimodal distribution with a piling of grades around 80% and 70%. Very few students receive grades above 92.5% and below 52.5%. The most frequent sixth grade grades are between 75% and 82.5%.

Grades predicting latent class membership. Latent class membership was regressed on fifth grade quarter 1 and 2 science grades using the R3STEP option of the AUXILIARY command in MPLUS v. 7.4 (Muthén & Muthén, 2012). Results of the multinomial logistic regression are shown in Table 3.2 as log odds in the first column and odds ratios in the second column. The reference group is the *High EV* latent class. Results indicated that fifth grade quarter 1 and 2 science grade is a significant predictor of log odds of being in the *Conflicted* class relative to being the *High EV* class ($\hat{\beta} = -0.704, p < 0.001$). In terms of odds ratios, a one unit increase in first half science grade (increasing one letter grade) is associated with, on average, a decrease in odds of 51% (*95% CI* = [0.38, 0.65]) of being in the *Conflicted* class relative to being in the *High Expectancy and Value* class. First half science grades were not a significant predictor of log odds of being in the *Low EV* class relative to the *High EV* class ($\hat{\beta} = -0.075, p > 0.05, 95\%\ CI\ OR = [0.67, 1.28]$). In other words, differences in grades in the first half of fifth grade were not predictive of being in the *High EV* class over the *Low EV* class or *vice versa*.

Predicted probabilities provide an alternative representation to log odds and odds ratios that are more easily interpreted because they present the estimated probability of a given outcome for an individual with particular values of predictors. Because there are only nine distinct values that mean first half fifth grade science grades can take on it is feasible to predict the probability of latent class membership in each of the three latent classes for each value of first half grades. The predicted probabilities for this analysis (Table 3.3, Figure 3.4A) indicate that a student who received the highest mean grade possible (i.e., 95%) is estimated to be observed in the *High EV* class 84.6% of the time, in the *Conflicted* class 4.8% of the time, and in the *Low EV* class 10.6% of the time. On average, students with the highest grades are much more likely to be observed in the *High EV* class. In contrast, for students with the lowest grades possible in quarters 1 and 2 (i.e., 55%), the probability that they would be in the *High EV* class (47.2%) and the *Conflicted* class (44.8%) is nearly the same, reflecting the association between lower grades and membership in the *Conflicted* class and not the *High EV* class. It is also important to note that for all possible fifth grade quarter 1 and 2 science grades that there is very little difference in the predicted probability of membership in the *Low EV* class, though it is highest for students who received grades ranging from 80% to 90%.

Figure 3.4b shows the estimated number of students in this sample that would be in each science grade-latent class combination. This was calculated by simply multiplying the predicted probabilities in table 3.3 by the number of students receiving each fifth grade quarter 1 and 2 science grade (Figure 3.3a). This figure helps illustrate that there are substantial numbers of students who were predicted to be in the *Conflicted* class among the students with the lowest grades as well as among students with higher grades because there are far more students who received grades in the middle of the grade range. At the highest part of the grade range, however, there are few students predicted to be in the *Conflicted* class. It is also notable that for each possible fifth grade quarter 1 and 2 grades there is a substantial portion of the students who are predicted to be in the *High EV* class, indicating that prior fifth grade science grades are not the sole determinant of subsequent motivation class membership.

Latent class membership predicting science achievement. The automatic BCH option of the AUXILIARY command in MPlus v7.4 was used to regress three measures of science achievement on latent class membership—5th grade quarter 4 science grade, 5th grade state standardized science assessment, and 6th grade science grade. Results are presented as mean achievement conditional on latent class membership (Table 3.4). For each outcome, an overall test of differences in means is presented, and, if the overall test is significant, pairwise comparisons of the means of each latent class are presented.

Fourth quarter science grades. Mean fourth quarter science grade was estimated to be 80.7% for the members of the High EV class, 74.4% for the Conflicted class, and 75.9% for the

Low EV class (Table 5.4). The overall chi-square test of mean differences in 5th grade fourth quarter science grades for each latent class was significant ($\chi^2 = 18.15$ (df = 2), p < 0.001), indicating that at least two means were significantly different from each other. Pairwise comparisons indicated that the mean fourth quarter grades of the *High EV* class members was significantly higher than the mean fourth quarter grades of members of both the *Conflicted* ($\chi^2 = 15.01$ (df = 1), p < 0.001) and *Low EV* classes ($\chi^2 = 5.366$ (df = 1), p <0.05). There was no significant difference in fourth quarter grades when comparing the *Conflicted* class to the *Low EV* class ($\chi^2 = 0.42$ (df = 1), p > 0.05). On average, students in the High EV class received grades that were 6.4 percentage points higher than students estimated to be in the Conflicted class and 4.8 percentage points higher than students estimated to be in the Low EV class. This is equivalent to about one half of one letter grade difference in fourth quarter grades. To facilitate comparison to the other achievement measures, differences in standardized units of fourth quarter grades are also shown in Table 3.4 and Figure 3.5. On this scale the mean fourth quarter grades of members of the *High EV* class is 0.54 standard deviations higher than the mean of students in the *Conflicted* class, and 0.41 standard deviations higher than the mean of students in the *Low EV* class.

Fifth grade state science assessment. Mean fifth grade science assessment score was estimated to be 361.5 for the members of the High EV class, 332.0 for the Conflicted class, and 358.22 for the Low EV class (middle panel, Table 3.4). The overall chi-square test of mean differences in 5th grade science assessment scores for each latent class was significant ($\chi^2 = 13.96$ (df = 2), p < 0.01), indicating that at least two means were significantly different from each other. Pairwise comparisons indicate that the mean fifth grade science assessment scores of the *High EV* members was significantly higher than the mean fifth grade science assessment of members of the *Conflicted* class ($\chi^2 = 13.90$ (df = 1), p < 0.001) and not significantly different from the mean for members of the *Low EV* class ($\chi^2 = 0.24$ (df = 1), p >0.05) classes. The difference in means between the *High EV* class and the *Conflicted* class amounts to 29.6 points on the scale of the assessment score or 0.71 standard deviations higher, on average, for members of the *High EV* class. There was also a significant difference in fifth grade science assessment score when comparing the *Low EV* class to the *Conflicted* class ($\chi^2 = 7.775$ (df = 1), p < 0.01). This difference amounts to 26.3 points on the scale of the assessment score or 0.63 standard deviations higher, on average, for members of the *Low EV* class.

Sixth grade science grades. Mean sixth grade science grades was estimated to be 75.7% for the members of the *High EV* class, 70.7% for the *Conflicted* class, and 75.6% for the *Low EV* class (bottom panel, Table 3.4). The overall chi-square test of mean differences in sixth grade science grades for each latent class was significant ($\chi^2 = 12.03$ (df = 2), p < 0.01), indicating that at least two means were significantly different from each other. Pairwise comparisons indicate that the mean sixth grade science grades of the *High EV* members was significantly higher than the mean sixth grade science grades of the *Conflicted* class members ($\chi^2 = 11.61$ (df = 1), p < 0.01) and not significantly different from the mean of the *Low EV* class members ($\chi^2 = 0.001$ (df = 1), p >0.05). The difference in means between the *High EV* class and the *Conflicted* class amounts to 4.97 grade percentage points or 0.45 standard deviations higher, on average, for members of the *High EV* class. There was no significant difference in mean sixth grade science grades when comparing the *Low EV* class to the *Conflicted* class ($\chi^2 = 3.02$ (df = 1), p > 0.05). However, the magnitude of this difference (4.92 percentage points or 0.44 s.d.) is about the same as the difference between *High EV* and *Conflicted*. The lack of significance here is likely due to the smaller size of the *Conflicted* and *Low EV* classes.

Discussion

The three latent classes identified in Study 1—*High EV, Conflicted,* and *Low EV*— were related to achievement in science on two types of measures, science classroom grades and a state standardized science assessment, prior and subsequent to the measurement of student motivation. Fifth grade science grades in the first half of the school year, before the motivation survey was administered, were used to predict latent class membership. In turn latent class membership was used to predict future science achievement. While these results do not represent causal effects, they contribute to our understanding of the association between expectancy-value-cost motivation constructs and science achievement.

Prior science grades predicting latent class membership. It was hypothesized that higher grades would be most predictive of being in the *High EV* latent class. Prior research has shown that past grades are positively associated with future task expectancy and task values (e.g., Chamorro-Premuzic et al., 2010; Eccles et al., 1983; Kosovich et al., 2015; Simpkins et al., 2006). This hypothesis was partially supported by the results. As expected, there was a positive significant relation between fifth grade quarter 1 and 2 science grades and log odds of being in the *High EV* class relative to the *Conflicted* class. The *High EV* class has higher levels of task expectancy and, to a lesser degree, task values, while the *Conflicted* class has lower levels of task expectancy and much higher levels of perceived cost.

In contrast, higher prior grades were not significantly related to membership in the *High EV* class over the *Low EV* class, despite the *High EV* class having higher levels of task expectancy and task values compared to the *Low EV* class, with both having similar levels of perceived costs. As discussed above, the theoretical pathway from prior grades to subsequent motivation is complex. The result that lower grades is not related to membership in a class with lower levels of task expectancy and task values, holding perceived costs at a relatively low value, could be reflective of an alternative pathway to internalizing higher prior grades as reflective of higher self-efficacy and lower barriers to success. Any number of personal and contextual factors could influence this. This study is not able to elucidate the specifics of these pathways.

The results also indicate that a student receiving higher prior grades has greater odds of being observed in the *Low EV* class compared to the *Conflicted* class. Taken together, these results reflect that students receiving lower prior grades are more likely to be observed in the class with the highest levels of perceived cost compared to students who received higher grades. Conversely, for students receiving higher grades, compared to their peers receiving lower grades, they were more likely to be observed in the classes with lower levels of perceived cost. Interestingly, however, the odds ratio of being in the class with higher task expectancy and task values (*High EV*) compared to a class with lower task expectancy and task values (*Low* EV) was no different for students with lower and higher prior grades. These results build on past variable-centered research by elucidating the heterogeneity of the relation between prior grades and subsequent motivation. The important role of perceived costs highlighted in recent years (e.g., Barron & Hulleman, 2015; Flake et al., 2015) is also supported. Further research in the heterogeneity of responses to prior achievement is warranted.

It is also important to note that prior achievement appears to be influential on subsequent motivation class, but predicted probabilities indicated that in the group of students with the lowest prior grades there was still a substantial portion who were later observed in the *High EV* latent class. Prior grades do not strictly determine subsequent motivation class membership. Classroom grades are just one achievement experience, albeit an important one, which students use, in conjunction with all of their other experiences, to inform their subsequent task expectancies, task values, and perceived costs.

Latent classes predicting subsequent achievement. It was hypothesized that membership in the *High EV* class would be related to the highest levels of achievement, the *Conflicted* class the lowest levels of achievement, and the *Low EV* class would be somewhere in between. In general, this hypothesis was supported, though there is some variation between the different achievement outcomes. For all three outcomes of fifth grade quarter 4 science grades, fifth grade state science assessment, and 6th grade grades, the estimated mean achievement was highest in the *High EV* class, followed by the *Low EV* class, and lowest in the *Conflicted* class.

However, only the differences in mean achievement between students in the *High EV* class and the *Conflicted* class were statistically significant for all three measures. In the case of fifth grade quarter 4 science grades, there was a significant difference in mean achievement between students in the *High EV* class and the *Low EV* class, but not between the *Low EV* class and the *Conflicted* class. In contrast, for both the fifth grade state science assessment and sixth grade grades, there was a significant difference in mean achievement between students in the *Low EV* class and the *Conflicted* class but no significant difference in mean achievement between students in the *High EV* class and the *Low EV* class. These differences could point to the different achievement contexts of each achievement measure and the survey items used to tap these motivation constructs. The task expectancy and perceived cost items used in this study are phrased in terms of students' current science class (e.g., "How sure are you that you can learn science this year?") while the task value items are phrased more generally about science (e.g., "How useful is science to you?"). The grades students receive in their fifth grade science class are the closest form achievement to the tasks described in the task expectancy and perceived cost items. Nonetheless, the expectancy-value-cost motivation classes predict science achievement across a variety of contexts.

Despite the differences in how the *Low EV* class predicts each achievement measure, the results indicate that students in the *High EV* class consistently achieve at higher levels than their peers and that students in the *Conflicted* class consistently achieve at lower levels. Membership in the *High EV* class, the most prevalent class, appears to be the most adaptive in terms of future achievement and this persists through to sixth grade. Membership in the *Conflicted* class appears to be the least adaptive class in terms of future achievement, and this also persists to achievement in the following school year. Since in study 1 it was found that students with an individualized education plan (IEP) were more likely to be in the *Conflicted* class these differences could be confounded by the distribution of students with IEPs across the three classes. To guard against this, these same analyses were also run without any students with IEPs and with only students with IEPs. The results were substantively the same for students without IEPs and the sample of only students with IEPs was too small to be able to make meaningful inferences. Motivation profiles similar to the *Conflicted* class are a potential target for interventions for all students.

It is generally accepted that both task expectancies and task values positively predict achievement and choice, but that task expectancies are better predictors of achievement and task values better predictors of choice (Wigfield et al., 2016). This pattern was seen in the study by Ruzek et al. (in process) using a somewhat overlapping but distinct sample as the current study. In this study, as in the current study, task expectancy, task values, and perceived cost items were correlated with achievement as expected. However, in an exploratory structural equation model with a task expectancy factor, a task values factor, and a perceived cost factor predicting science achievement on the same fifth grade state science assessment, the task expectancy factor was a positive significant predictor of achievement, perceived cost was a negative significant predictor of achievement, and task values was not a significant predictor of achievement. The person-centered approach taken in the current study helps to elucidate the underlying patterns of how motivation constructs co-occur with achievement. Task expectancy is highest in students in the *High EV* class and is lower and of a similar level in students in both the *Conflicted* class and the *Low EV* class. The *High EV* class also consistently achieves at higher levels. This leads to a clear positive relation between task expectancy and achievement. In contrast, higher task values are not as clearly predictive of higher achievement. It is the case that the *High EV* class exhibits the highest probability of endorsing high values and is associated with, on average, the highest levels of achievement. However, compared to the *Low EV* class, the *Conflicted* class exhibits much higher probabilities of endorsing higher levels of task values and is predictive of achievement that is consistently lower or equivalent to that predicted by membership in the *Low EV* class. For this sample, this attenuates the relation between task values and achievement. Finally, the large negative relation between perceived cost and achievement is attributable to members of the *Conflicted* class, the one class with appreciably higher probability of endorsing higher perceived costs, being consistently predictive of lower achievement. The other two classes have low probability of endorsing higher perceived costs and both are predictive of higher achievement, on average. In the aggregate this results in the negative relation observed between perceived costs and achievement in this study and, potentially, in other similar studies (e.g., Conley, 2012; Kosovich et al., 2015).

That the relation between each expectancy-value-cost motivation construct and subsequent achievement is not as straightforward as correlations would suggest is not inconsistent with theory. Early versions of Expectancy-Value Theory (e.g., J. W. Atkinson,

1957) were explicit in the hypothesized interaction of task expectancy and task values. It was theorized, and supported by evidence from laboratory experiments that manipulated task expectancy, that motivation for a task was highest when both task expectancy and task value were high. This interaction is theorized in modern Expectancy-Value Theory (e.g., Barron & Hulleman, 2015; Eccles et al., 1983; Wigfield et al., 2016), but, until recently, underexplored. Several researchers have modeled latent interactions of expectancy-value-cost factors in predicting choice (e.g., Nagengast et al., 2011) and achievement (e.g., Guo et al., 2016; Trautwein et al., 2012). Trautwein and colleagues (2012) found significant interactions between self-concept and each of four types of task values (with perceived cost included as a type of task value) in predicting achievement in math and English. There was a positive interaction between self-concept and each of intrinsic value, utility value, and reverse-coded perceived cost. While this study did not model all types of task values at once, these results are consistent with the findings in the current study, though the current study points to the particular importance of perceived costs. Perceived costs were also found to be particularly important in the study by Guo an colleagues (2016), who modeled the unique contribution of each type of task value (with perceived costs considered a type of task value) above and beyond the contribution of a global task values factor in predicting math achievement. When self-concept, global task values, and each type of task value were included in a model predicting math achievement, only the self-concept and perceived costs factors were significant predictors. When interactions were added to the model, the interactions between self-concept and global task values and between self-concept and perceived costs (reverse coded) were positive significant predictors of achievement. Both of these studies indicate a positive interaction between expectancy-related beliefs and task values, which is reflected in the current study in the *High EV* class predicting the highest levels of achievement. The second study indicates a particular importance of perceived costs in predicting achievement above and beyond global task values, which is reflected in the current study in the *Conflicted* class predicting lower achievement than the other two classes, on average, despite having higher task values than the *Low EV* class. These results suggest that perceived costs are a crucial component of understanding students' achievement behaviors.

As with prior person-centered research that relates task expectancy, task values, and/or perceived costs to achievement, the intra-individual patterns described by the latent classes in study 1 were able to predict meaningful differences in achievement. In her study of 7th grade math motivation clusters, Conley (2012) included measures of achievement goals in addition to measures of expectancy-value-cost motivation making direct comparisons difficult. However, a contrast between high-perceived-cost and low-perceived-cost clusters indicated that, on average, the high perceived cost clusters had lower achievement. Perez et al. (2019) described three latent profiles of task expectancy, task values, and perceived costs in first year college science students and related profile membership to STEM GPA after one and four years of college. The three profiles described in this study were qualitatively different from the current study because the profile with the highest level of perceived costs, *Moderate All*, also has the lowest levels of task expectancies and task values. Nonetheless, membership in the *Moderate All* class was associated with the lowest STEM GPA after one and four years of college. The growing number of person-centered studies demonstrates the value in describing extant patterns of intraindividual motivation and those patters associations with important achievement behaviors. They also point to the important role of perceived costs in differentiating motivation types and in predicting achievement.

Tables

Table 3.1 *Sample Size, Mean, and Standard Deviations of Achievement Measures; and Correlations of EVC Items and Achievement Measures*

	Expec.	**V1 Import.**	**V2 Utility**	**V3 Intrinsic**	**C1 Effort**	**C2 Emot.**	**5th Q1 & 2**	**5th Q4**	**5th State Science**	**6th**
EVC Items, Dichotomized										
Task Expectancy	-									
Task Values 1, Importance	***0.37***	**-**								
Task Values 2, Utility	***0.45***	***0.63***	**-**							
Task Values 3, Intrinsic	***0.49***	***0.67***	***0.55***	**-**						
Cost 1, Effort	***-0.34***	-0.001	**-0.17**	**-0.14**	-					
Cost 2, Emotional	***-0.35***	**-0.2**	-0.1	***-0.29***	***0.37***	-				
Science Achievement										
5th Grade Quarter 1 & 2 Science Grades	***0.16***	0.02	**0.13**	-0.02	***-0.19***	***-0.27***	-			
5th Grade Quarter 4 Science Grades	***0.30***	0.12	***0.18***	**0.14**	***-0.14***	***-0.2***	***0.58***	-		
5th Grade State Science Assessment	***0.25***	0.02	**0.16**	0.02	***-0.32***	***-0.25***	***0.42***	***0.35***	-	
6th Grade Science Grades	***0.17***	-0.02	***0.16***	-0.01	***-0.15***	**-0.11**	***0.37***	***0.4***	***0.41***	-
n	860	860	860	860	860	860	851	824	582	765
% = 1/Mean (SD)	89%	91%	87%	85%	30%	23%	77.46 (10.39)	79.13 (11.63)	356.54 (41.90)	74.86 (11.05)
Minimum	0	0	0	0	0	0	55	55	240	50
Maximum	1	1	1	1	1	1	95	95	474	100

Note: Significant correlations indicated by **bold** ($p < 0.05$) and ***bold italicized*** ($p < 0.01$) text. Correlations between pairs of EVC items are tetrachoric correlations; between EVC items and achievement measures are point-biserial; and between achievement measures are Pearson. Expec. = Expectancy; V = Value; Import. = Importance; C = Cost; Emot. = Emotional

Table 3.2 *Regression of Latent Class Membership on Fifth Grade Quarter 1 & 2 Grades*

Latent Class	**Log Odds Estimate (SE)**	**Odds Ratio [95% CI]**
Conflicted (Low E, High C)		
Intercept	-1.46* (0.21)	
First Half Science Grade	-0.704* (0.139)	0.49 [0.38, 0.65]
Low EV		
Intercept	-1.926* (0.195)	
First Half Science Grade	-0.075 (0.164)	0.93 [0.67, 1.28]

Note: High EV class is the reference group; E = Expectancy; V = Value

* *$p < 0.001$*

Table 3.3 *Predicted Probabilities: 5th grade Quarter 1&2 Science Grades Predicting Latent Class Membership*

5th Grade Q1&2 Science Grade	Predicted Probability of Latent Class Membership in: *High EV*	*Conflicted*	*Low EV*
95%	84.6%	4.8%	10.6%
90%	82.6%	6.7%	10.8%
85%	80.0%	9.2%	10.8%
80%	76.7%	12.5%	10.8%
75%	72.6%	16.8%	10.6%
70%	67.5%	22.3%	10.2%
65%	61.5%	28.8%	9.7%
60%	54.6%	36.4%	8.9%
55%	47.2%	44.8%	8.0%

Table 3.4 *Estimated Mean Science Achievement Conditional on Latent Class Membership*

Latent Class	Estimated Mean (SE)	Standardized Mean	Overall χ^2 (df)	1) High EV vs 2) Conflicted χ^2 (df)	1) High EV vs 3) Low EV χ^2 (df)	2) Conflicted vs 3) Low EV χ^2 (df)
5th Grade Science Q4 Grade						
1) High EV	80.7 (1.14)	0.13	18.15*** (2)	15.05*** (1)	5.366* (1)	0.415 (1)
2) Conflicted	74.4 (1.71)	-0.41				
3) Low EV	75.9 (2.05)	-0.28				
5th Grade Science Assessment						
1) High EV	361.54 (2.94)	0.12	13.96 ** (2)	13.90*** (1)	0.24 (1)	7.775** (1)
2) Conflicted	331.95 (7.52)	-0.59				
3) Low EV	358.22 (7.12)	0.04				
6th Grade Science Grade						
1) High EV	75.7 (0.75)	0.08	12.03** (2)	11.61 ** (1)	0.001 (1)	3.02 (1)
2) Conflicted	70.7 (1.31)	-0.37				
3) Low EV	75.6 (2.25)	0.07				

Note: E = Expectancy; V = Value.
$* p < 0.05$, $** p < 0.01$, $*** p < 0.001$

Figures

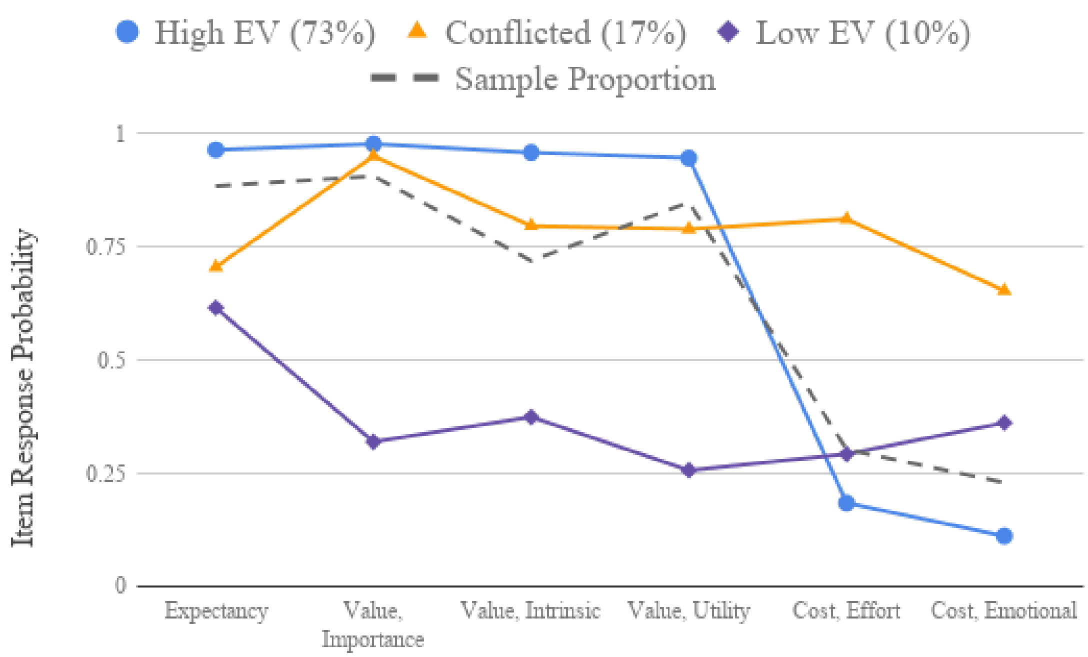
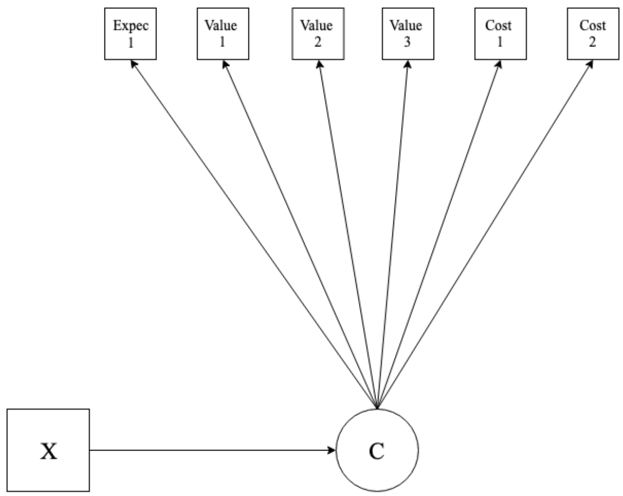


Figure 3.1 Results of study 1: profile plots of three latent expectancy-value-cost science motivation classes, class prevalences, and sample proportions of item responses.
Note: E = Expectancy, V = Value

A



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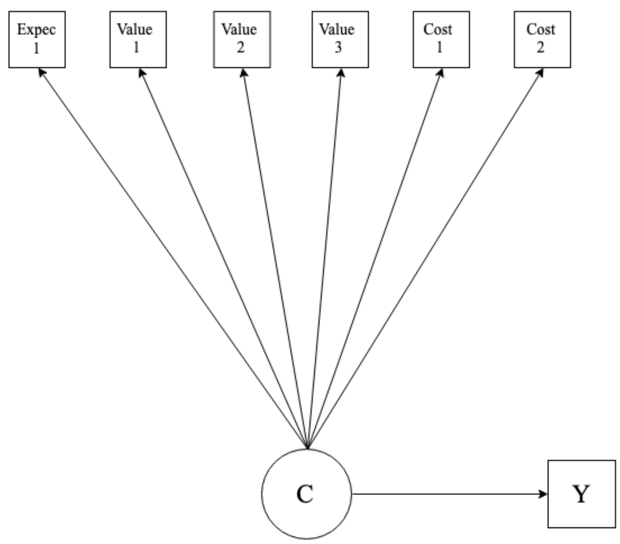


Figure 3.2 Latent class regression models.
A) Regression of latent class variable C on predictor X. Model for research question 3.1. B) Distal outcome model of latent classes predicting distal outcome Y. Model used for research question 2.2.
Note: Circle represents latent categorical variable. Squares represent observed variables. Arrows connecting variables represent regression. Actual number of parameters estimated depends on number of latent classes estimated and item-response probabilities, which are not shown in this diagram.

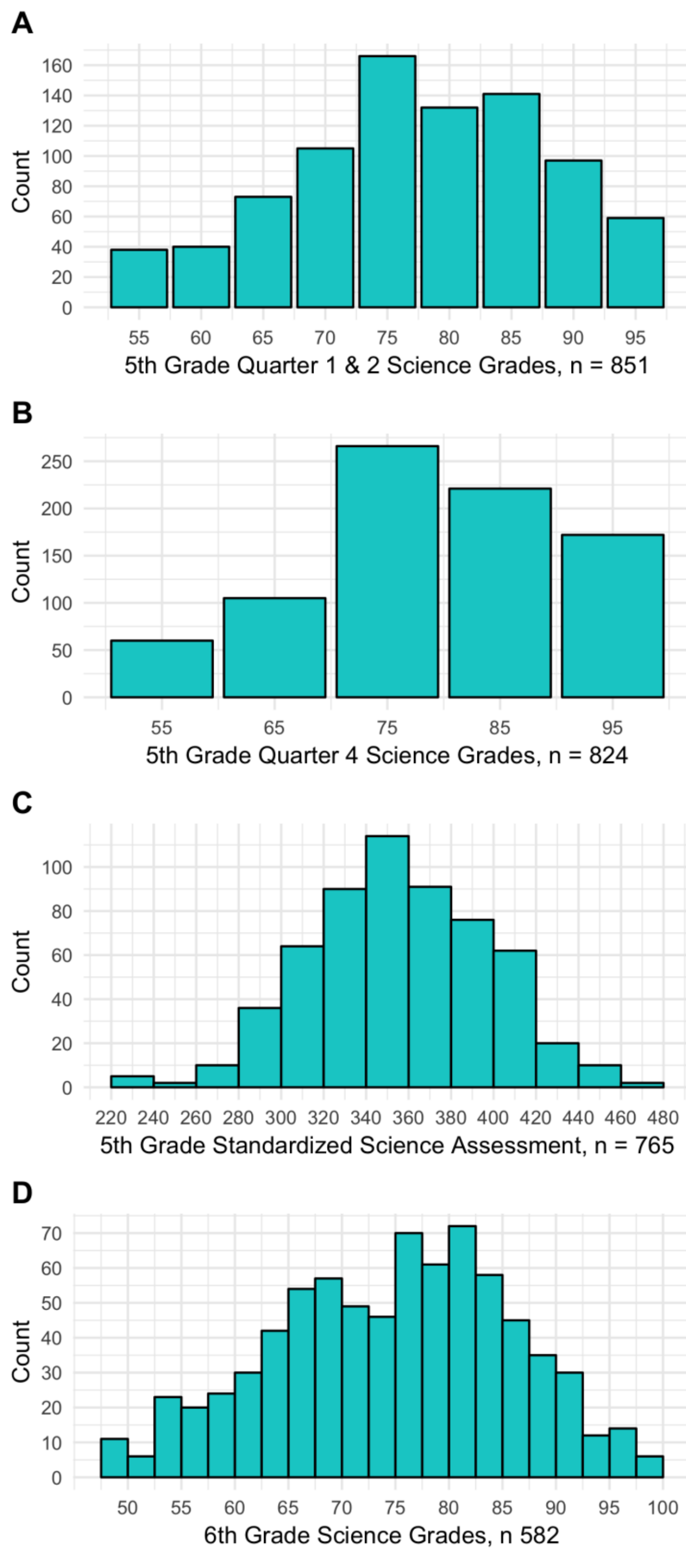
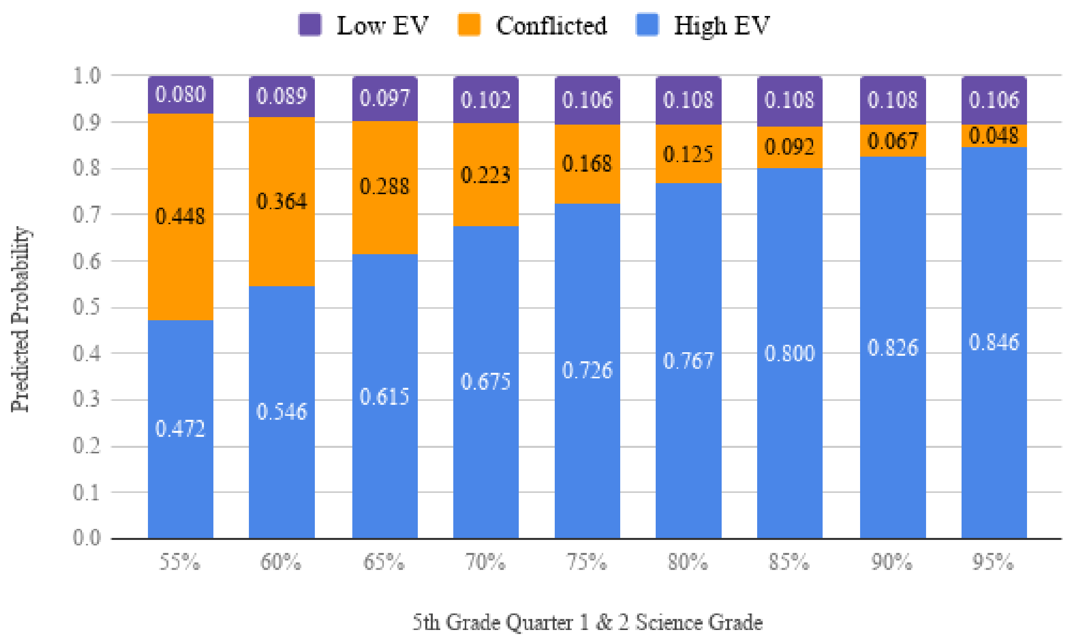


Figure 3.3 Distribution of science achievement measures.
A) Bar chart of 5th grade quarter 1 & 2 science grades. B) Bar chart of 5th grade quarter 4 science grades. C) Histogram of 5th grade state science assessment scaled scores. D) Histogram of 6th grade science grades.

A



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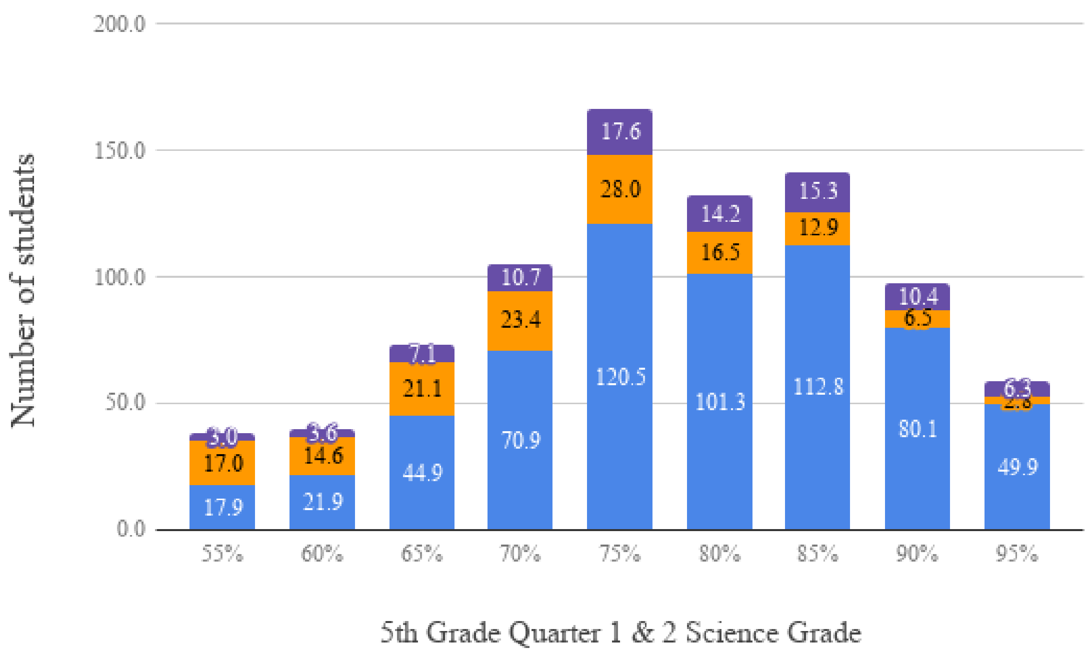

Figure 3.4 Predicted latent class membership conditional on prior science grade.
A) Predicted probabilities of latent class membership, conditional on prior grade received. B) Predicted number of students in each latent class, conditional on prior grade received.
Note: Note: E = Expectancy, V = Value

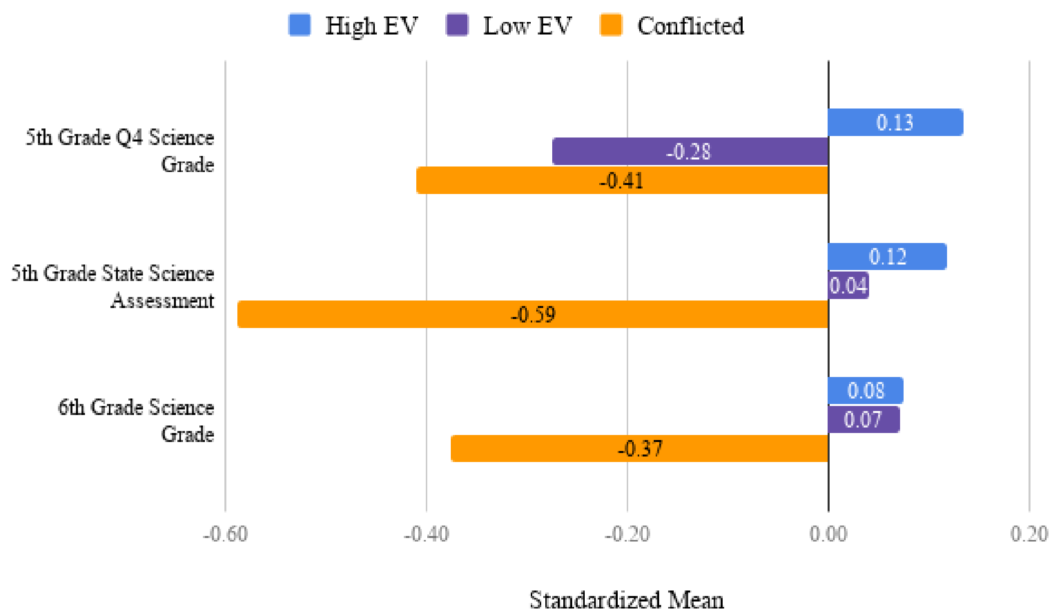

Figure 3.5 Standardized mean science achievement, conditional on latent class membership.
Note: Note: E = Expectancy, V = Value

Chapter 4—Study 3: Latent Transitions between Science Motivation Classes

Research questions 3.1 and 3.2 concern the estimation of latent classes and transitions between latent classes from fourth to fifth grade. This study will expand on the sample used in studies 1 and 2 to include fourth grade students.

One of the most consistent findings of research on expectancy-value-cost motivation is that the level of task expectancy, task value, and perceived cost for academic domains decreases as students get older (e.g., Archambault et al., 2010; Ball, Huang, Cotten, & Rikard, 2017; Chamorro-Premuzic et al., 2010; Chittum & Jones, 2017; Eccles et al., 1989; Wigfield et al., 1991). This has been shown in both longitudinal samples and cross-sections. With few exceptions (e.g., Archambault et al., 2010; Wang et al., 2017) this research focuses on the mean levels of these constructs within a sample of students over time, for longitudinal studies, or cross-sections of student of different ages at a single point in time. If there are students whose task expectancy or task value increases while the bulk of their peers' decreases, most research obscures these groups of students. Additionally, how task expectancy and task value relate to each other within a student over time is seldom examined (Archambault et al., 2010; Denissen et al., 2007; Kosovich et al., 2017; Wang et al., 2017). Thus, we can say that, on average, task expectancy and task value decrease over time, but do not know if there are students for whom both increase or for whom one increases over time while the other decreases. The research on similar questions for cost is even sparser. If we are to understand how a child might become more or less engaged in their science education then an improved understanding of how these constructs relate within a child over time and how that may influence their performance and trajectory in science is needed.

This study extends the results of study 1, which identified latent classes of expectancy-value-cost motivation in a sample of urban elementary students at a single point in time, to a longitudinal analysis of how latent motivation class or status changes over time and how student characteristics predict changes over time. This chapter presents the research questions, relevant literature review, hypotheses, and method for this analysis.

Research Questions

RQ 3.1) How is class membership in fourth grade related to class membership in fifth grade? What is the likelihood of changing between any two statuses from one year to the next?

RQ 3.2) How are transitions between statuses different across student characteristics and educational status?

Literature Review

A consistent finding of expectancy-value-cost motivation research is that mean levels of expectancy and related beliefs, and task values tend to decrease as students get older (Wigfield, 2015). For example, in a longitudinal sample covering first though twelfth grades, declines in self-competence (related to task expectancy) and task value were observed in math, language arts, and sports (Jacobs, Lanza, Osgood, Eccles, & Wigfield, 2002). Recent research has examined important heterogeneity in these trajectories, indicating that amid this general decline there are different rates of decline and, in some cases, increases in expectancy-related beliefs and task values over time (e.g., Archambault et al., 2010; Musu-Gillette et al., 2015; Watt, 2004).

Heterogeneity of trajectories in task expectancy and task value. Using the same longitudinal data set as Jacobs et al., (2002), Archambault et al., (2010) found seven latent growth trajectories of self-concept of ability (related to task expectancy) and task values (measured by general importance and utility value) in literacy. While all of the trajectories showed a net decline from first to twelfth grade, they revealed a great deal of difference in those trajectories. Four of the seven trajectories could be characterized as consistent declines in task values, though the starting points and total change over time was different for each of those four task value trajectories. The other three trajectories show initial declines in both self-concept and task values with a turnaround at some point in their education. The "transitory declining trajectory" and the "low trajectory" both show self-concept and task values for literacy turn around and start increasing around 7th grade. The early decline trajectory, however, turns around at about 9th grade. Musu-Gillette et al., (2015) similarly found three latent trajectories in each of self-concept (related to task expectancy) in math, interest in math (related to intrinsic value), and importance of math (related to general task value), in 421 students over the course of 4th through 12th grade. The three trajectories for each construct indicated that the overall decline in each construct observed in the sample was comprised of trajectories that had different starting points, rates of decline (or stability in some cases), and shapes.

Research examining heterogeneity of trajectories in expectancy and task value does not always show consistent declines. Wang et al. examined trajectories of self-concept (related to task expectancy) and task values (measured by intrinsic value, utility value, and importance) in physical science for 699 predominantly European-American students over the course of 7th to 12th grade (2017). Seven joint latent trajectories of physical science self-concept and task value were determined to best represent the data. In this sample, as observed in other samples, the overall pattern of change was a decline in self-concept and task value for physical science. However, two of the trajectories remained stable across the time span of the study, and one consistently increased from 7th to 12th grade. The stable trajectories, "stable high" and "stable moderate," were estimated to represent over half of the sample at 26.6% and 36.2% of the sample, respectively. The steadily increasing trajectories were estimated to represent only 4.1%

of the sample. Without this type of research the 4.1% of students whose motivation in physical science was increasing over middle and high school would be obscured by the overall trend.

The studies described above that model joint trajectories of task expectancy and expectancy-related beliefs and task values (e.g., Archambault et al., 2010; Wang et al., 2017) describe a common relation between expectancy-related beliefs and task value. For each latent pair of joint trajectories of these two constructs, the trajectories are often quite similar. In other words, it is rare to see latent trajectories where the level of expectancy-related beliefs and task values are all that different at any given time. This could explain the generally high correlations observed between expectancy-related beliefs and task values in other research (e.g., Conley, 2012; Eccles & Wigfield, 1995; Kosovich et al., 2015; Trautwein et al., 2012). These constructs are theorized to influence each other over time. Indeed, there is evidence that these constructs become more correlated as students get older (e.g., Denissen et al., 2007) and even that they change together over the course of a college semester (e.g., Kosovich et al., 2017).

An important omission from this longitudinal research is the inclusion of a measure of perceived cost, which appears to be an important contributor to heterogeneity in student expectancy-value-cost motivation. Several studies have used cluster analysis or latent class analysis to uncover common patterns of motivational beliefs in samples of students (e.g., Andersen, 2013; Andersen & Chen, 2016; Andersen & Cross, 2014; Conley, 2012; Phelan et al., 2017; Roeser & Peck, 2003). In all of these studies several classes (or clusters) of motivation were identified and, in general, within a class, the level of task expectancy and task values were about the same, which also aligns with the coupling of these two constructs reported above. However, one study (Conley, 2012), included a measure of perceived cost in finding clusters of achievement goal and expectancy-value-cost motivation for math in 1,870 seventh grade students. As with the other studies, expectancy-related beliefs and task values tended to track together in a cluster, but the perceived cost measure distinguished clusters that had similar levels of other constructs.

To my knowledge there is scant research examining the change in elementary students expectancy-value-cost motivation over time. Furthermore, the longitudinal studies that do exist in other domains and/or age ranges most frequently do not include a measure of perceived cost, which appear to be important in explaining heterogeneity in student motivation (e.g., Conley, 2012) and in predicting important achievement outcomes (Barron & Hulleman, 2015; Flake et al., 2015). As a result the interplay of task expectancy, task value, and perceived cost over time is not well understood. When these constructs are included in studies predicting achievement in a variety of domains, they are often included in separate models because of collinearity issues in linear regression (e.g., Guo et al., 2016; Marsh et al., 2005; Trautwein et al., 2012). Person-centered methods like latent class analysis can avoid this issue by finding common patterns, or classes, of several constructs and using those classes to predict achievement outcomes. Latent transition analysis is a longitudinal extension of latent class analysis, which estimates latent classes at each time point simultaneously and estimates how membership in one class predicts membership at the next time point. In this study I used latent transition analysis to understand what patterns of science task expectancy, task value, and perceived cost exist at one point in time for each of fourth and fifth grade and how students move between patterns from one year to the next.

Hypotheses

The latent classes described in study 1 include data from fifth grade students who were identified as Black/African-American and as neither Latinx nor English language learners. The sample in that study was reduced to this subset because measurement invariance could not be established across several subgroups. The current study expands to include fourth and fifth graders, including a large subset of students who are observed in both years. This larger sample may have different results from study 1. Nonetheless, a reasonable assumption is that the latent classes found in this study will be similar to those found in study 1. I hypothesized that the latent classes in this study will be similar to those described in study 1—a *High EV* class, *Low EV* class, and a *Conflicted* class. My hypotheses regarding latent transitions were informed by this first hypothesis and the findings (described above) that task expectancy and task value tend to decrease as students get older, though there are exceptions among a small subset of students. I hypothesized that students will tend to stay in their prior year latent status or that they will transition to a status with lower levels of task expectancy and task value (e.g., from *High EV* to *Low EV* or *Conflicted*; or from *Conflicted* to *Low EV*. A smaller fraction of students will transition to statuses with higher levels of task expectancy and task value (e.g, from *Low EV* to *High EV* or *Conflicted*; or from *Conflicted* to *High EV*). The empirical literature has less to say about perceived cost, though theory would predict that higher levels of perceived cost would result in transitions to classes with lower levels of task expectancy and task value, which aligns with the hypothesis that there will be a greater number of students transitioning from the *Conflicted* class to the *Low EV* class than to the *High EV* class.

Method

This study used a sample collected as a part of the SABES project and includes all of the students and survey responses from the 860 students in study 1 as well as an additional 846 fourth and fifth grade students from the same schools. SABES is a National-Science-Foundation funded Math Science Partnership grant that aims to improve STEM education in nine Baltimore

City Public School System elementary and elementary/middle schools through a partnership between the school district and a research university (Johns Hopkins University). SABES also recruited five schools to serve as comparison schools, for a total of 14 schools involved in the project. The scope of the project expanded in each year, starting with four schools in 2013 and adding three intervention and two comparison schools in each subsequent school year. In the final year, 2016-17, two of the comparison school decided to not participate. As a part of the grant a student survey was administered in the participating SABES and comparison schools in the spring of each school year. The motivation data presented in this study were collected in the participating schools in the 2014-15, 2015-16, and 2016-17 school years.

Student surveys were administered by trained researchers and research assistants. Through an agreement with the school district, consent to survey all students was granted. Students were able to opt out of any of the surveys or other data collection activities at any time. While some students refused to participate, this was rare. Over the course of the two school years that span this study, about 1,900 students were surveyed at least once as a fourth and/or fifth grade student. In total, these approximately 1,900 students were comprised of three grade-level cohorts (Figure 4.1). As shown in Figure 4.1, cohort 3 was in fifth grade in 2014-15 and was only surveyed in that year. Cohort 2 was surveyed as fourth graders in 2014-15 and as fifth graders in 2015-16. Cohort 1 was surveyed as fourth graders in 2015-16 and as fifth graders in 2016-17. Over the two years of data collection 1,094 fourth graders and 1,489 fifth graders responded to the survey. Student IDs from the district were used to link student observations over time and to demographic and educational information from the school district. Some student observations were not matched to their district ID and as a result will not be included in the analysis. A small number of students were observed in the same grade in both school years, indicating they repeated the grade. So that these students do not appear as two observations in a single grade level, one of their observations was randomly dropped from the sample. These sample restrictions resulted in a loss of 10% of observations. As a result, the analytic sample consists of 961 fourth grade student observations and 1,361 fifth grade student observations, a total of 2,322 student-year observations. In cohort 2 there were 279 students were observed in fourth and fifth grade and in cohort 1 there were 337 student observed in fourth and fifth grade. Thus, the analytic sample consists of 1,706 individual students.

Table 4.1 shows student gender/sex, race/ethnicity, English language learner (ELL) status, and individualized education plan (IEP) status of students in the sample. The sample of participating students was nearly split between male- and female-identified students (n_{female} = 861, 50.5%). Students were primarily identified as Black (n = 1,136; 67%) and Latinx (n = 485, 28%), including 22 (1.3%) students who were identified as both Black and Latinx. Because race and ethnicity identification are not mutually exclusive, the two right columns of Table 4.1 show a cross-tabulation of the Latinx variable with the other descriptive variables. This shows that while 517 (30%) students in the sample identified as white, only 82 of those students were identified as non-Latinx white students. This distribution of student race/ethnicity in this sample differs from elementary schools in the district as a whole. In 2016, 79% of students were identified as Black, 10% Latinx, 9% white non-Latinx, and 2% as Asian, Pacific Islander, American Indian, or multiple race.

Students in the sample were largely eligible for the federal free- and reduced- price lunch program (n = 1,632; 96%). In comparison, in 2016, 72% of elementary students in the district were eligible ("2016 Maryland Report Card," 2016). In the sample 230 (13.5%) students were identified as having an individualized education plan, which is an indicator of receiving special education services ("2016 Maryland Report Card," 2016). This is similar to the district rate of 13% for elementary students in 2016. In the sample 299 (17.5%) students were identified as English language ("2016 Maryland Report Card," 2016). This is up to three times larger than the district rate of 6% for elementary students in 2016 ("2016 Maryland Report Card," 2016).

Analysis. Latent transition analysis is a longitudinal extension of latent class analysis. In contrast to latent class analysis, latent transition analysis conceives of the hypothesized latent categories as (potentially) time-variant and thus it is suggested to refer to them as statuses rather than classes (Collins & Lanza, 2013). To maintain consistency throughout this dissertation I will continue to use the term "latent class" but this is not to imply that class membership is a trait rather than a state. In addition to estimating the likelihood of membership in a latent status (or class in latent class analysis) and the conditional item response probabilities, latent transition analysis also estimates transition probabilities, which are estimates of the likelihood of transitioning to a latent status at time $t + 1$ conditional on latent status membership at time t.

Model specification. Latent transition models were estimated using MPlus version 7.4 (Muthén & Muthén, 2012) using full-information maximum likelihood (FIML) and robust maximum likelihood estimation (MLR). Maximum likelihood estimation of mixture models occurs in two steps. In the first step random initial stage starting values for parameters are generated. Several optimization iterations are carried out for each set of randomly generated starting values. The results of the first stage iterations with the largest log likelihood are used as starting values in several final stage optimizations. All models were run with at least 100 sets of initial stage random starting values, 20 initial stage optimization iterations for each set of starting values, and 20 final stage optimizations. The maximum likelihood procedure can find local likelihood maxima rather than the global maximum. This can be guarded against with a larger number of sets of starting values, initial stage iterations, and final stage iterations. Each model was checked to ensure that the maximum loglikelihood value repeated over several iterations. If this did not occur, the number of initial sets of starting values, initial stage iterations, and final stage iterations was increased up to 4,000, 80, and 200, respectively. If a model did not repeat the maximum loglikelihood under these conditions, it was deemed non-identified and was not considered as a valid result.

A series of models were estimated to determine the number of classes that best reflected the data as well as whether the latent class model was invariant across the two time points. A path diagram of these models (excluding the covariate X and the regression of latent classes on X) is shown in Figure 4.2. These models posit unobserved latent class variables—C4 in fourth grade and C5 in fifth grade, with k classes each—which predict student responses on the six dichotomized motivation survey items. At each time point, item response probabilities are estimated for each of the *k* classes such that, conditional on class membership, student responses to each item are independent. Additionally, transition probabilities are determined from a multinomial logistic regression of latent class membership in C5 on class membership in C4.

Time invariance. It is common practice to constrain item-response probabilities to be the same at each time point because this reduces model complexity and, importantly, keeps the meaning of each latent class at each time point the same. However, if this is not a reasonable constraint then the model can be misestimated and those estimates can be misleading. Since motivation develops over time it is not a given that during the time frame of this study that latent classes at each time point will be the same. As a result, a test of invariance over time will be conducted. To do this, two models will be estimated and compared. Model 1, an unconstrained model, will allow item-response probabilities to vary at each time point. Model 2 will constrain item-response probabilities to be the same at each time point. The two models will be compared with a χ^2 difference test and with their AIC and BIC values. A non-significant result to the χ^2 test will indicate that there is no significant improvement in model fit in the unconstrained model. In the interest of parsimony, the constrained time-invariant model would be retained. Lower values of AIC and BIC would indicate better model fit as well. If the time-variant model provides substantial improvement in model fit, then this will have implications about how task expectancy, task value, and perceived cost develop over time within children. Care will have to be taken in interpreting the results because a time-variant model implies that the meaning of the latent statuses changes over time, but nonetheless could provide support for the hypothesis that the types of science motivation extant in this sample of students changes as student get older.

Number of latent classes. Beginning with two latent classes, models with increasing numbers of latent classes will be estimated until model fit does not improve or the model will not converge. For each number of classes, *k*, two models were estimated. The first model, denoted "I" for invariant, constrained the item response probabilities in fourth and fifth grade to be the same. The second model, denoted "V" for variant, allowed the item response probabilities to vary across time points. All models will be compared using Aikake information criteria (AIC) and the Bayesian information criteria (BIC), with lower values indicating the better fitting model. Nested models, those with the same number of latent statuses but differing in the time-invariance, will be compared with a χ^2 difference test as well. Parsimony and meaningful interpretation will also influence model choice. Finally, model fit was assessed by examining standardized residuals of predicted cell counts and actual cell counts.

Estimation. Models were estimated in MPLUS version 7.4 (Muthén & Muthén, 2012) using the TYPE = MIXTURE option in the ANALYSIS command. To adjust standard errors for the clustering of students in classrooms the TYPE = COMPLEX option in the ANALYSIS command and the CLUSTER option in the VARIABLE command was used as well. Models were be estimated using full information maximum likelihood, which uses all the available information in the indicator variables to estimate the model.

Measurement invariance for student groups. Measurement invariance across each of the groupings of male/female, Black/Latinx, general education student/student with IEP, and English language proficient/English language learner were conducted to determine if the item-response probabilities in the latent transition model differ across each of these important groups of students. For the race/ethnicity group comparisons, students in the “other” group were excluded from the analysis since this group is comprised of students from several different racial/ethnic backgrounds. Additionally, 22 students in the sample were identified as both Black and Latinx. These students were excluded for group invariance testing because they could reasonably be placed in both groups. For each subgrouping, a constrained and an unconstrained model was estimated and compared. In the constrained model, the estimated item-response probabilities were held equal across the grouping variable while in the unconstrained model the item-response probabilities were allowed to vary between the groups. The models were compared using a χ^2 difference test. Finding no significant difference between the models indicated that there was support for the similar meaning and interpretation of the latent classes for each subgroup. If there was a significant difference between the groups, then there is support for a different interpretation of the latent classes for each group. As described below, measurement variance between Latinx and non-Latinx students was found. As a result, differences in model estimates were examined to determine if the item response probabilities estimated for a specific item appeared to be the source of the differences between the groups.

Partial invariance was established by constraining all item response probabilities to be the same for Latinx and non-Latinx students except for the task expectancy probabilities. This partially invariant model was used for subsequent analyses when possible.

Group differences in latent class prevalences. To determine whether latent class prevalences at each time point differ by gender, ethnicity, English language learner status, and individualize education plan status, four models in which latent class membership at each time point is regressed on each covariate were estimated. These models were compared to the final latent transition model without these regression terms using a likelihood ratio test to determine if the model in which the covariate predicted class prevalence provided significantly better fit than the constrained model.

Group differences in latent class transitions. To determine whether gender, ethnicity, English language learner status, and individualize education plan status moderates the transitions between latent classes at each time point four models in which the estimates of the regression coefficients of latent class membership in fifth grade on latent class membership in fourth grade were allowed to vary across groups were estimated. When such models were estimated using the partially invariant task expectancy model, which uses the MULTIGROUP setting and Latinx as a GROUPING variable in MPlus, these models would not converge properly because of empty cells in the joint distribution of the latent class variable, the Latinx grouping, and the covariate of interest, except in the case of Latinx as a covariate. To simplify the joint distribution, these same models were estimated using the fully invariant latent transition model. While prior analyses indicated that there were differences in the latent class model between Latinx and non-Latinx students, the differences in the models were small and did not change the substantive interpretation of the latent classes. Furthermore, as described below in the results section, there was no difference in latent class prevalences and transition probabilities based on Latinx group membership. While returning to the fully invariant latent transition model obscures the differences in latent classes between Latinx and non-Latinx students, the differences are minor and this change allowed the investigation of differences in class prevalences and transitions for the other subgroups. This approach allowed the estimation of the model regressing latent transitions on gender. However, for the English language learner, and individualized education plan models, the same issue, empty cells in the joint distribution of the latent class and the covariate of interest distribution, persisted. A final attempt was made using the manual 3-step procedure to estimate latent transition regression models (Asparouhov & Muthén, 2014). In the first step of this procedure the latent class model is estimated at each time point. In the second step students are place in their most likely latent class at each time point based on the estimated model and the measurement error for each latent class is recorded. In the third step a latent transition model in which the most likely latent class membership for each student at each time point is used as a class indicator variable with fixed error rates equal to the estimated measurement error recorded in step 2 is estimated. The 3-step approach was used for the English language learner model and the individualized education plan model. The individualized education plan model was estimated properly but the English language learner model did not converge properly. As a result the moderation of latent transitions by English language learner status was not assessed. The gender, Latinx, and individualized education plan latent transition regression models were compared to the final latent transition model without these regression terms using a likelihood ratio test.

Results

Figure 4.3 shows the distribution of responses to the six motivation survey items for the fourth and fifth grade samples. The orange portion of each bar reflects the frequency of responses for the subset of 616 students observed in both fourth and fifth grade. In both years student responses to the task expectancy and task values are predominantly high (3 and above) and responses to the perceived cost items are predominantly, though to a lesser extent, low (2 and below). Direct comparisons of the fourth and fifth grade samples are misleading because of different total sample sizes in each grade level. Focusing, then, on just the students observed in both grade levels is instructive to understand how student responses change over time. In general, the relative distribution of student responses for each item is similar between fourth and fifth grade. In the case of the task expectancy and task value items, there is a slight decrease in higher value responses and an increase in lower value responses, indicating that, on average, students observed twice in this sample responded with lower levels of task expectancy and task values in fifth grade compared to fourth grade. Conversely, the opposite pattern is seen when comparing responses to the perceived cost items for the students observed twice in this sample, indicating that, for them, perceived cost increases from fourth to fifth grade.

For the analysis in this study, as in the prior studies, the six motivation survey items were dichotomized. Table 4.2 shows the proportion of responses that were recoded to 1 for each survey item at each time point. The first column indicates the percent of dichotomized responses equal to 1 for all students who responded to that item in that grade level and the second column reflects the percent for only the students who responded in both years. A large majority (> 87%) of students in both grades responded to the task expectancy and task value items at high values, which were recoded as 1. Less than a third of students responded with high values for the perceived cost items at both time points.

Table 4.2 also shows tetrachoric correlations for the dichotomized survey responses. Looking within a grade level, the variables are related to each other as expected. For all observed fourth or fifth graders (correlations above the diagonal), task values items were most highly correlated with each other (0.49 to 0.73 in fourth grade, and 0.56 to 0.69 in fifth grade) and perceived cost items were most highly correlated with each other (0.56 in fourth grade and 0.50 in fifth grade). Task expectancy and task value items were positively correlated (0.20 to 0.48 in fourth grade and 0.40 to 0.46 in fifth grade). Task expectancy and perceived costs were negatively correlated (-0.15 and -0.30 in fourth grade and -0.28 and -0.34 in fifth grade). Task values and perceived costs were negatively correlated (-0.07 and -0.53 in fourth grade and -0.05 and -0.36 in fifth grade). These relations were consistent when looking within a grade level for the students who were observed twice.

These relations did not hold when looking at correlations between time points in this sample. The lower left quadrant of correlations in table 4.2 shows the tetrachoric correlations between each item in fourth grade and each item in fifth grade. These correlations reflect the complex relations between motivation constructs over time. For the task expectancy and general task value items the correlation of the same item with itself at the other time point was larger in magnitude than any correlation with any other variable. For example, the correlation of the task expectancy item in fourth grade with the task expectancy item in fifth grade was 0.35, which was higher than any fifth grade item's correlation with fourth grade task expectancy (-0.30 to 0.16) and any fourth grade items correlation with fifth grade task expectancy (-0.10 to 0.23). For other items this was not the case. For example, the effort cost item in fifth grade was most correlated with the task expectancy item in fourth grade (-0.30) rather than with the same effort cost item in fifth grade (0.23). There are several such relations, reflecting the need for models that can reflect the complex interplay of these constructs within and across time

Number of classes and time invariance. Latent transition models with two, three, or four classes and that were either time-variant (Models 2V, 3V, 4V) or time-invariant (Models 2I, 3I, 4I) were estimated. The loglikelihood was not replicated in both Model 4I and 4V even with 4000 sets of initial stage starting values, 80 initial stage optimization for each set of starting values, and 400 final stage iterations. Thus the models with four classes were not considered. Table 4.3 shows model fit information for the estimated latent class models. Across models, the AIC and BIC were lowest for Model 3I. A likelihood ratio test comparing the nested Model 3I to Model 3V indicated that the time-variant model did not provide significantly better fit than the time-invariant model (Table 4.4, Test 1: $G^2 = 26.93$, $df = 18$, $p > 0.05$). Model 3I, the 3-class time-invariant model, was selected as the final model.

Latent classes. The top panel of table 4.5 shows the estimated item response probabilities and latent class prevalences for each time point from Model 3I. Figure 4.4 visualizes the item response probabilities with profile plots for each estimated latent class. The results in the current study were largely similar to the three latent classes described in study 1—*High EV*, *Conflicted*, and *Low EV*. The one difference between the two models that compelled a different substantive interpretation was that for students in the *Low EV* class in the current study, the probability of endorsing higher values of emotional cost was on par with the *Conflicted* class. For this reason, in this study, the *Low EV* class is referred to as the *Low EV High EmC* class. Otherwise the substantive interpretation of each class is similar to study 1.

In this study, as in study 1, the *High EV* class was the most prevalent (4th grade: 65%; 5th grade: 60%), the *Conflicted* class was the next most prevalent (4th grade: 27%; 5th grade: 30%) and the *Low EV High EmC* class was the least prevalent (4th grade: 8%; 5th grade: 10%). Notably, the prevalence of the *High EV* class decreased by 5% from fourth to fifth grade while the prevalence for the *Conflicted* and *Low EV High EmC* class increased by 3% and 2%, respectively. While this does not reflect a large amount of net change in latent class membership from fourth grade to fifth grade, the estimated latent transition probabilities indicate a more dynamic process.

Latent transition probabilities. The estimated latent transition probabilities are shown in the middle panel of table 4.5. The probabilities indicate the probability of being observed in each latent class in fifth grade conditional on membership in fourth grade. These results indicate that the most likely outcome, given membership in a particular latent class in fourth grade, is membership in the same class in fifth grade for all three latent classes. Membership in the *High EV* class is the most stable with an estimated 73% probability that, given membership in the *High EV* class in fourth grade, a student will be observed in the *High EV* class in fifth grade. Students in the *High EV* class in fourth grade are estimated to have a 20% probability of being observed in the *Conflicted* class and a 7% change of being observed in the *Low EV High EmC* class in fifth grade. The *Conflicted* class had a lower level of stability with an estimated 56% of students appearing in the *Conflicted* class in fifth grade, conditional on membership in that class in fourth grade. Students in the *Conflicted* class in fourth grade were estimated to have a 37% probability of being observed in the *High EV* class and an 8% chance of being observed in the *Low EV High EmC* class in fifth grade. The *Low EV High EmC* class had the lowest stability with only 42% of students estimated to be in that class in 5th grade, conditional on membership in fourth grade. Students in the *Low EV High EmC* class in fourth grade were estimated to have a 32% probability of being observed in the *High EV* class and a 26% chance of being observed in the *Conflicted* class in fifth grade.

Measurement invariance. A series of models testing the measurement invariance of Model 3I across subgroups of students in the sample were estimated. All models had 3 latent classes and time invariance. For each grouping variable (gender, race/ethnicity, ELL status, IEP status) two nested models were estimated. The first variant model allowed the item response probabilities to differ between members of each group. The second invariant model constrained the item response probabilities in each group to be the same. A likelihood ratio test was used to determine if the more complex variant model fit the data significantly better than the invariant model. Results of these tests (see Table 4.4) indicated that for gender (Test 2: $G^2 = 19.11$, $df = 18$, $p > 0.05$), English language learner status (Test 3: $G^2 = 20.34$, $df = 18$, $p > 0.05$), and individualized education plan status (Test 4: $G^2 = 28.35$, $df = 18$, $p > 0.05$) there was no significant difference in model fit across these groupings. However, the likelihood ratio test comparing a model which allows item response probabilities to vary between Black and Latinx students to a model which constrains the item response probabilities to be the same indicated that the variant model provided significantly better fit to the data (Test 5: $G^2 = 30.23$, $df = 18$, $p < 0.05$). These results indicate that for both genders, for both students who are English language proficient and students who are English language learners, and for both students with and without an individualized education plan, the measurement model was the same and that for Black and Latinx students different latent class models better represented the data.

Partial invariance. A partial invariance model in which only the item response probability for the task expectancy item was allowed to vary between the Black and Latinx groups was tested against the fully variant ethnicity model. A likelihood ratio test indicated that the fully invariant model in which all item response probabilities were allowed to vary across groups did not provide significantly better fit than the partially invariant task expectancy model (Test 6: $G^2 = 14.08$, $df = 15$, $p > 0.05$). These models did not include the students in the other race/ethnicity group nor did it include students who were identified as both Black and Latinx. To reincorporate these students into the sample, measurement invariance between the Black and the other group was tested using the subsample of students not identified as Latinx ($n = 1{,}221$). However, the other group sample size was small and the model did not converge because of sparseness. Instead, the entire sample was recombined and a partially invariant model with the task expectancy item response probabilities allowed to vary between the Latinx group and the non-Latinx group (i.e., the full sample with Latinx as the grouping variable) was tested against a variant model in which all of the item response probabilities were allowed to vary between the Latinx group and the non-Latinx group. A likelihood ratio test indicated that the variant model in which all item response probabilities were allowed to vary between the Latinx group and the non-Latinx group did not provide significantly better fit than the partially invariant model (Test 7: $G^2 = 13.96$, $df = 18$, $p > 0.05$). Furthermore, the item response probabilities for the task expectancy item did not differ drastically between the model estimated from the entire sample and the model estimated from the sample that excluded the other race/ethnicity group. As a result the partially invariant model estimated from the entire sample was retained.

The bottom panel of Table 4.5 shows the estimated item response probabilities for this final partially invariant model estimated with the entire sample. The first row indicates the task expectancy item response probabilities for the non-Latinx and the Latinx variant. Figure 4.4b visualizes the latent classes as profile plots of item response probabilities for each latent class.

The task expectancy item response probabilities for the non-Latinx group is indicated with a solid connecting line and those for the Latinx group are indicated with a dashed connecting line. In general the Latinx variant model does not differ much from the model for the rest of the sample. The task expectancy item response probabilities are lower in the Latinx variant (0.92, 0.81, 0.41) compared to the non-Latinx group (0.98, 0.82, 0.63) with the largest difference between the item response probabilities the *Low EV High EmC* class (Latinx: 0.41; non-Latinx: 0.63).

Latent transition interaction with student variables. As described in the method section above, several modeling approaches were used to assess if the variables Latinx, female, English language learner, or individualized education plan interact with the regression of latent class membership in fifth grade on latent class membership in fourth grade. First, two models using the partially invariant task expectancy measurement model were estimated. The first regressed latent class membership at each time point on Latinx. The second model built on the first to include the moderation of latent transitions by the Latinx variable as well. Both models were compared to the partially invariant task expectancy latent transition model. Likelihood ratio tests indicated that latent class membership did not differ at each time point (Test 8: $G^2 = 8.88$, $df = 4$, $p > 0.05$) and that Latinx did not moderate transition between classes. Allowing Latinx to moderate the latent transitions did not provide significantly better fit compared to the partially invariant model (Test 9: $G^2 = 13.28$, $df = 8$, $p > 0.05$).

For each of the remaining student variables, female, English language learner, and individualized education plan, a similar set of two models were estimated for each variable and compared to a constrained model in which latent class prevalences and transitions were not influenced by the covariate. Modeling issues required the use of a different base model than the partially invariant task expectancy model used in the Latinx analysis described above (see Method for details). In the case of the individualized education plan and English language learner variables, a 3-step approach (Asparouhov & Muthén, 2014) was used, though the same issue persisted for the English language learner model. Likelihood ratio tests comparing each model to a base latent transition model indicated that there was no significant difference in latent class prevalences at each time point (Test 10: $G^2 = 6.10$, $df = 4$, $p > 0.05$) and in latent transitions (Test 11: $G^2 = 8.93$, $df = 8$, $p > 0.05$) between boys and girls in the sample. Similarly, there was no difference in latent class prevalences at each time point (Test 12: $G^2 = 8.92$, $df = 4$, $p > 0.05$) and in latent transitions (Test 13: $G^2 = 10.74$, $df = 8$, $p > 0.05$) between students with individualized education plans and students without individualized education plans in the sample.

Discussion

This study explored whether latent expectancy value cost science motivation classes could be identified in fourth and fifth grade science students and, if identified, describe them and changes in class membership over time. Three such classes, *High EV*, *Conflicted*, and *Low EV High EmC*, were identified. These classes were quite similar in their qualitative interpretation as those described in study 1. Measurement invariance was assessed across important subgroups of students in the sample. The latent class model was invariant across gender, English language learner status, and individualized education plan status. This indicates that, for these students, membership in a given latent class for a student in one group has the same substantive interpretation as for a student in another group. Invariance of all parameters for Latinx and non-Latinx students was not present. However, a partially invariant model, which allowed only the item response probabilities for the task expectancy items to vary between the two groups provided fit similar to a variant model.

Latent transition analysis was then performed to regress latent class membership in fifth grade on latent class membership in fourth grade. Latent class prevalences at both time points were estimated to be similar, with slightly lower prevalence of the *High EV* class and slightly higher prevalence of both the *Conflicted* and *Low EV High EmC* in fifth grade compared to fourth grade. While membership in any of the three classes was most predictive of membership in the same class one year later, this analysis revealed changes in motivation class belied by the small changes in class prevalence from fourth to fifth grade. Finally, there were no significant differences in class prevalences and transition probabilities based on student characteristics.

Latent classes. While the transition from one latent class to another over time is the main focus of this study, those transitions have little meaning without describing the latent classes themselves. The three latent classes described in this study are quite similar to the latent classes described in study 1 and, importantly, reflect qualitatively distinct constellations of expectancy-value-cost motivation. Of the myriad possible combinations of these motivation constructs, three common patterns emerged. These patterns are valuable both because they indicate the extant patterns of motivation that are in a sample as well as indicate the patterns that are not present in a sample. This better reflects the nature of psychological constructs like task expectancy, task values, and perceived cost which are theorized to simultaneously reside within each individual and influence each other over time. And when examining how these constructs change over time in a sample, a person-centered approach such as this prevents extrapolation outside of the data, which can occur in variable-centered analyses, especially when one focuses on several constructs at once.

Latent transitions. The estimated changes in latent class membership described in this study reveal different levels of stability and change for each latent class. Past variable-centered research supports the notion that, on average, prior task expectancy and task values predict subsequent task expectancy and task values (e.g., Jacobs et al., 2002; Marsh et al., 2005) though these relations are not always found (Steinmayr & Spinath, 2009). The stability of the *High EV* class supports these findings as well. Membership in the *High EV* class was the most stable from fourth grade to fifth grade, with 73% of students in this class predicted to be observed in the same class in fifth grade. In the aggregate, then, students with higher levels of task expectancy and task values in fourth grade are most likely to be observed with similarly high task expectancy and task values in fifth grade. However, students observed in the *High EV* class in fourth grade are also predicted to transition to the *Conflicted* class 20% of the time. This result indicates that for some students with high task expectancy and task values in fourth grade they are observed in a class that appears quite similar on task expectancy and task values, which are relatively high in the *Conflicted* class, but have a distinctively higher level of perceived costs. A smaller portion of students (7%) in the *High EV* class in fourth grade are estimated to transition to the *Low EV High EmC* class. This particular transition, while a small proportion, would contribute to the average declines in task expectancy and task values over time consistently observed in past research (e.g., Archambault et al., 2010; Jacobs et al., 2002; Wigfield et al., 1991, 1997). The transition from *High EV* to *Low EV High EmC* also represents a change to a motivational state with higher perceptions of cost. Given the negative association of perceived cost with achievement described in study 2, these findings suggest that exclusion of perceived cost from longitudinal studies of motivation could omit important motivational changes within students with real consequences for student achievement.

The *Conflicted* class exhibited some stability as well—56% of students in this class in fourth grade were estimated to remain there in fifth grade. Both early and recent theorizing about perceived cost (e.g., Barron & Hulleman, 2015; Eccles et al., 1983) suggests that perceived cost negatively influences both task expectancies and task values. That would suggest that students in the *Conflicted* class in fourth grade would be likely to appear in the *Low EV High EmC* class. However, this is the least likely transition (8%) for students estimated to be in the *Conflicted* class in fourth grade. Instead students in the *Conflicted* class are most likely to remain in that class or to transition to the *High EV* class a year later. These findings could be explained by an alternate explanation. Perhaps perceiving a task as valuable, perceiving it to be important, useful, and enjoyable, while that task is also difficult may activate perceptions of cost like effort cost and emotional cost. Whereas for students who do not perceive value in a task, they are much less likely to perceive cost, especially in the form of emotional cost. More research examining the personal and contextual factors that influence perceived cost is needed.

The *Low EV High EmC* class is the least stable class in this sample. Less than half of the students (42%) estimated to be in this class in fourth grade remain there in fifth grade. For students in the *Low EV High EmC* class in fourth grade that do not remain in it, 32% are estimated to be in the *High EV* class and 26% are estimated to be in the *Conflicted* class in fifth grade. These latter two transitions reflect a pattern that is contrary to average declines in task expectancy and task values observed in past research (e.g., Jacobs et al., 2002; Wigfield et al., 1997). However, in person-centered research on expectancy-value-cost motivation trajectories small groups of students with increasing, stable, or reversing trajectories have been described (e.g., Archambault et al., 2010; Wang et al., 2017).

These findings illustrate the value of taking a person-centered approach to understanding complex intrapersonal phenomena such as achievement motivation. The latent classes and transitions described here reflect many of the macro patterns observed in past expectancy-value-cost motivation research. However, the classes also reveal heterogeneity among students that is obscured by variable-centered research. Furthermore, the heterogeneity of the transitions reveal a diverse set of motivational experiences some of which are predicted by theory and some of which are underexplored in the literature. The inclusion of perceived cost in this study continues to underscore the important variation captured by this understudied facet of expectancy-value-cost motivation.

Tables

Table 4.1 *Sample Demographic and Educational Status Variables*

	Entire Sample	Non-Latinx	Latinx
	n = 1706	*n* = 1221	*n* = 485
	Count (%)	Count (%)	Count (%)
Female	861 (50.5)	626 (51.3)	235 (48.5)
Black	1136 (66.6)	1114 (91.2)	22 (4.5)
White	517 (30.3)	82 (6.7)	435 (89.7)
Asian	25 (1.5)	20 (1.6)	5 (1.0)
American Indian, Pacific Islander, Alaskan Native, Multiple Race	28 (1.6)	5 (0.4)	23 (4.7)
Latinx	485 (28.4)	0 (0.0)	485 (100.0)
FRL	1632 (95.7)	1182 (96.8)	450 (92.8)
ELL	299 (17.5)	25 (2.0)	274 (56.5)
IEP	230 (13.5)	191 (15.6)	39 (8.0)
4th Grade	961 (56.3)	667 (54.6)	294 (60.6)
5th Grade	1,361 (79.8)	948 (77.6)	413 (85.2)
Observed in 4th and 5th Grade	616 (36.1)	394 (32.3)	222 (45.8)

Note: FRL = qualified for federal free- and reduced-price lunches; ELL = Enlgish language learner; IEP = individualized education plan

Table 4.2 *Prevalences of and Intercorrelations among Dichotomized Expectancy-value-cost Motivation Survey Items*

	Entire Sample	**Observed in 4th and 5th Grade**	**4th Grade**						**5th Grade**					
			E	**V1**	**V2**	**V3**	**C1**	**C2**	**E**	**V1**	**V2**	**V3**	**C1**	**C2**
4th Grade	n = 1706	n = 616												
Expectancy	90%	90%	-											
Value Item 1, General	93%	93%	***0.314***	-										
Value Item 2, Utility	88%	89%	**0.203**	***0.511***	-									
Value Item 3, Intrinsic	90%	91%	***0.484***	***0.726***	***0.491***	-								
Perceived Cost 1, Effort	27%	28%	***-0.286***	-0.101	-0.068	***-0.258***	-							
Perceived Cost 2, Emotional	22%	22%	***-0.357***	***-0.277***	***-0.259***	***-0.533***	***0.557***	-						
5th Grade			**E**	**V1**	**V2**	**V3**	**C1**	**C2**	**E**	**V1**	**V2**	**V3**	**C1**	**C2**
Expectancy	88%	88%	***0.345***	0.126	0.057	**0.236**	-0.102	-0.102	-					
Value Item 1, General	91%	92%	0.155	***0.456***	**0.253**	***0.311***	-0.059	-0.145	***0.403***	-				
Value Item 2, Utility	89%	88%	0.152	**0.273**	0.164	0.117	-0.160	-0.102	***0.411***	***0.636***	-			
Value Item 3, Intrinsic	87%	88%	0.088	***0.322***	**0.217**	**0.209**	-0.052	0	***0.455***	***0.690***	***0.555***	-		
Perceived Cost 1, Effort	31%	29%	-0.299	0.066	0.085	0.156	0.23	0.159	***-0.275***	-0.050	***-0.152***	***-0.175***	-	
Perceived Cost 2, Emotional	24%	23%	-0.152	**-0.208**	-0.101	-0.159	***0.196***	***0.218***	***-0.341***	***-0.273***	***-0.313***	***-0.358***	0.502	-

Note: Significant correlations indicated by **bold** ($p < 0.05$) and ***bold italicized*** ($p < 0.01$) text. Sample size varies slightly for each item based missing responses. Tetrachoric correlations are based on all available data for each pairwise combination of variables.

Table 4.3 *Comparison of Model Fit*

Model	Log Likelihood	Free Parameters	AIC	BIC	SABIC	Entropy
2I	-5404.172	15	10838.344	10919.973	10872.32	0.574
2V	-5386.908	27	10827.817	10974.748	10888.972	0.532
3I	-5285.809	26	10623.618	10765.108	10682.509	0.546
3V	-5271.338	44	10630.675	10870.119	10730.337	0.544

Table 4.4 *Nested Model Comparisons Using Satorra-Bentler Scaled Likelihood Ratio Tests*

		Unconstrained Model			Constrained Model					
Test	Sample	Log-likelihood	# Free Parameters	Scaling Correction	Log-likelihood	Scaling Correction	# Free Parameters	Scaled Chi Square	df	*p*-value
1) Time Invariance	Entire	-5271.338	44	1.073	-5285.809	1.0719	26	**26.93**	**18**	**0.08**
2) Gender Invariance	Entire	-6453.744	53	1.0508	-6462.924	1.0971	35	**19.11**	**18**	**0.39**
3) ELL Invariance	Entire	-6052.946	53	1.1747	-6067.817	1.027	35	**20.34**	**18**	**0.31**
4) IEP Invariance	Entire	-5931.318	53	1.0591	-5947.073	1.0321	35	**28.35**	**18**	**0.057**
5) Latinx/Black Invariance	Black & Latinx	-5836.664	53	1.049	-5853.107	1.029	35	**30.23**	**18**	**0.035**
6) Partial Latinx/Black Invariance (Expectancy)	Black & Latinx	-5836.664	53	1.049	-5844.210	1.040	38	**14.08**	**15**	**0.52**
7) Partial Invariance Latinx (Expectancy)	Entire	-6279.315	53	1.0716	-6286.888	1.0662	38	**13.96**	**15**	**0.53**
LTA Regression										
8) Class prevalence vary by Latinx	Entire	-6289.014	34	1.073	-6293.863	1.0704	30	**8.88**	**4**	**0.064**
9) Class prevalence and transitions by Latinx	Entire	-6286.888	38	1.0662	-6293.863	1.0704	30	**13.28**	**8**	**0.10**
10) Class prevalence vary by Gender	Entire	-5282.389	30	1.0756	-5285.809	1.0719	26	**6.22**	**4**	**0.18**
11) Class prevalence and transitions by Gender	Entire	-5280.49	34	1.0999	-5285.809	1.0719	26	**8.93**	**8**	**0.35**
12) Class prevalence vary by IEP	Entire	-2502.192	13	1.0119	-2506.822	1	9	**8.92**	**4**	**0.063**
13) Class prevalence and transitions by IEP	Entire	-2501.453	17	1	-2506.822	1	9	**10.74**	**8**	**0.22**

Note: Entire sample n = 1.706; Black & Latinx sample n = 1,577

Table 4.5 *Latent Transition Model Estimates of Item Response Probabilities and Transition Probabilities for Model 3I and Latinx Variant Model*

Model 3I			
Probability that Item = 1…	*Conditional on membership in…*		
Item	High EV	Conflicted	Low EV High EmC
Expectancy	0.96	0.82	0.59
Value Item 1, General	0.98	0.97	0.36
Value Item 2, Utility	0.95	0.89	0.43
Value Item 3, Intrinsic	0.97	0.88	0.26
Perceived Cost 1, Effort	0.11	0.67	0.36
Perceived Cost 2, Emotional	0.04	0.55	0.50
Estimated Class Prevalences in…	High EV	Conflicted	Low EV High EmC
4th Grade	65%	27%	8%
5th Grade	60%	30%	10%
	Probability of transition to 5th grade status...		
from 4th grade status...	High EV (5th)	Conflicted (5th)	Low EV High EmC (5th)
High EV (4th)	0.73	0.20	0.07
Conflicted (4th)	0.37	0.56	0.08
Low EV High EC (4th)	0.32	0.26	0.42
Model 3I Latinx Variant			
Probability that Item = 1…	*Conditional on membership in…*		
Item	High EV	Conflicted	Low EV High EmC
Expectancy/Latinx Variant	0.98/0.92	0.82/0.81	0.63/0.41
Value Item 1, General	0.98	0.97	0.35
Value Item 2, Utility	0.95	0.89	0.43
Value Item 3, Intrinsic	0.97	0.88	0.25
Perceived Cost 1, Effort	0.11	0.67	0.36
Perceived Cost 2, Emotional	0.04	0.57	0.49

Figures

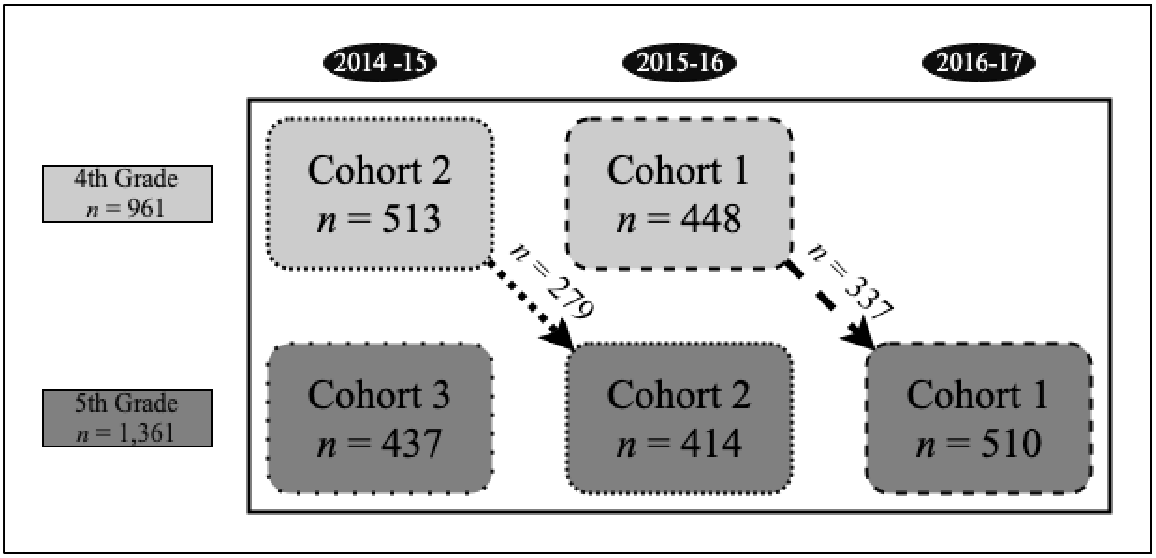

Figure 4.1 Data collection design.
Sample sizes indicated for each grade-level by school year combination and, on the diagonal arrows, the number of students within a cohort observed at both time points.

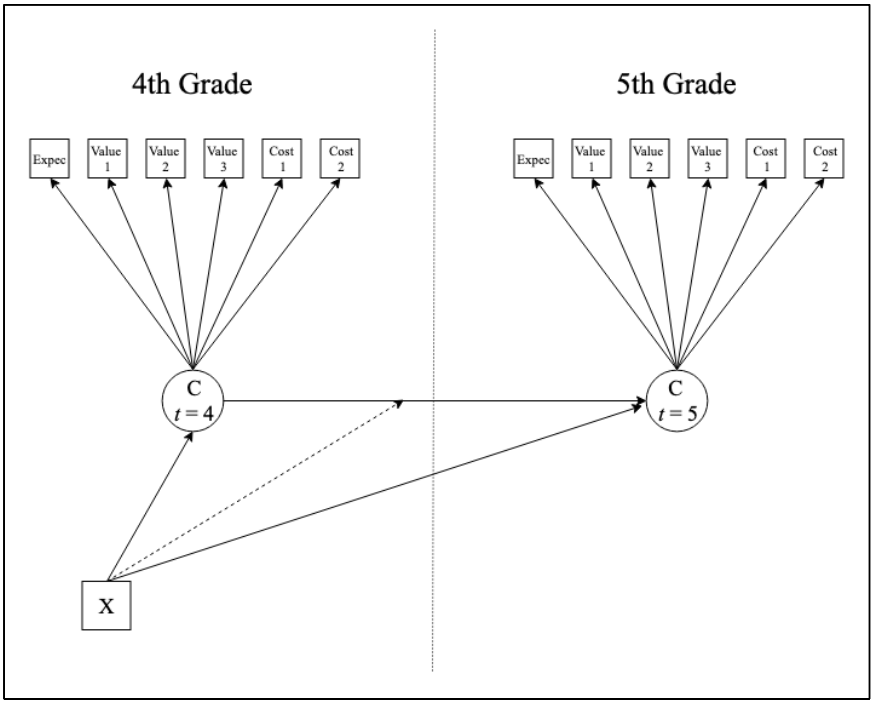

Figure 4.2 Depiction of latent transition analysis model.
Circles represent latent variables, squares represent observed variables, solid arrows represent direct relationships, and the dashed arrow represents the moderation of the relation between latent statuses at each time point by a covariate X.

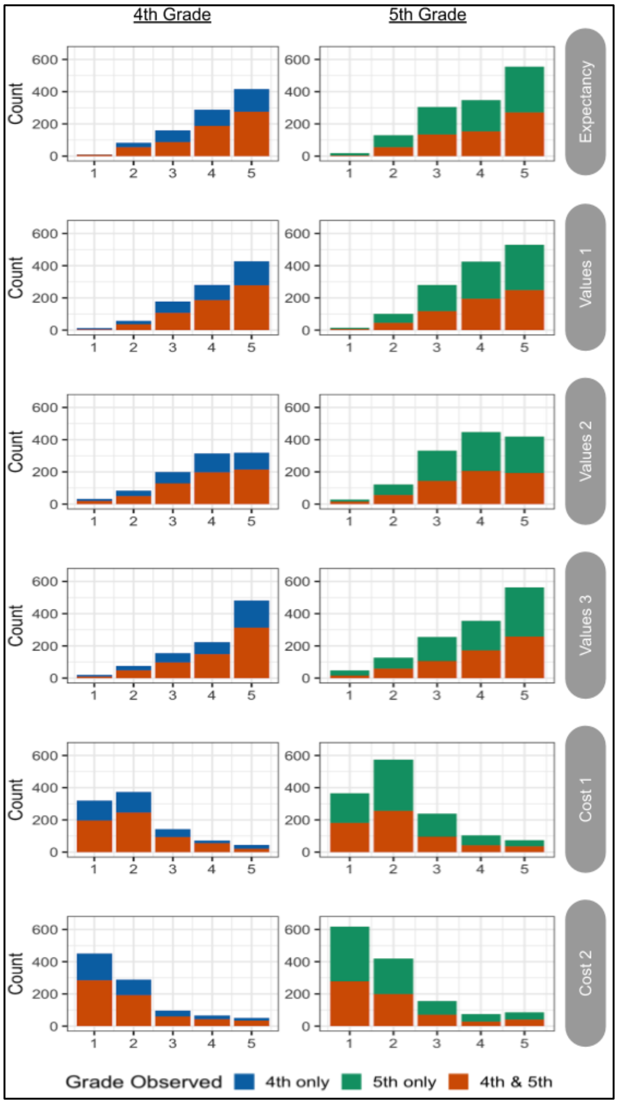

Figure 4.3 Distribution of expectancy, value, cost survey responses in the fourth and fifth grade samples.

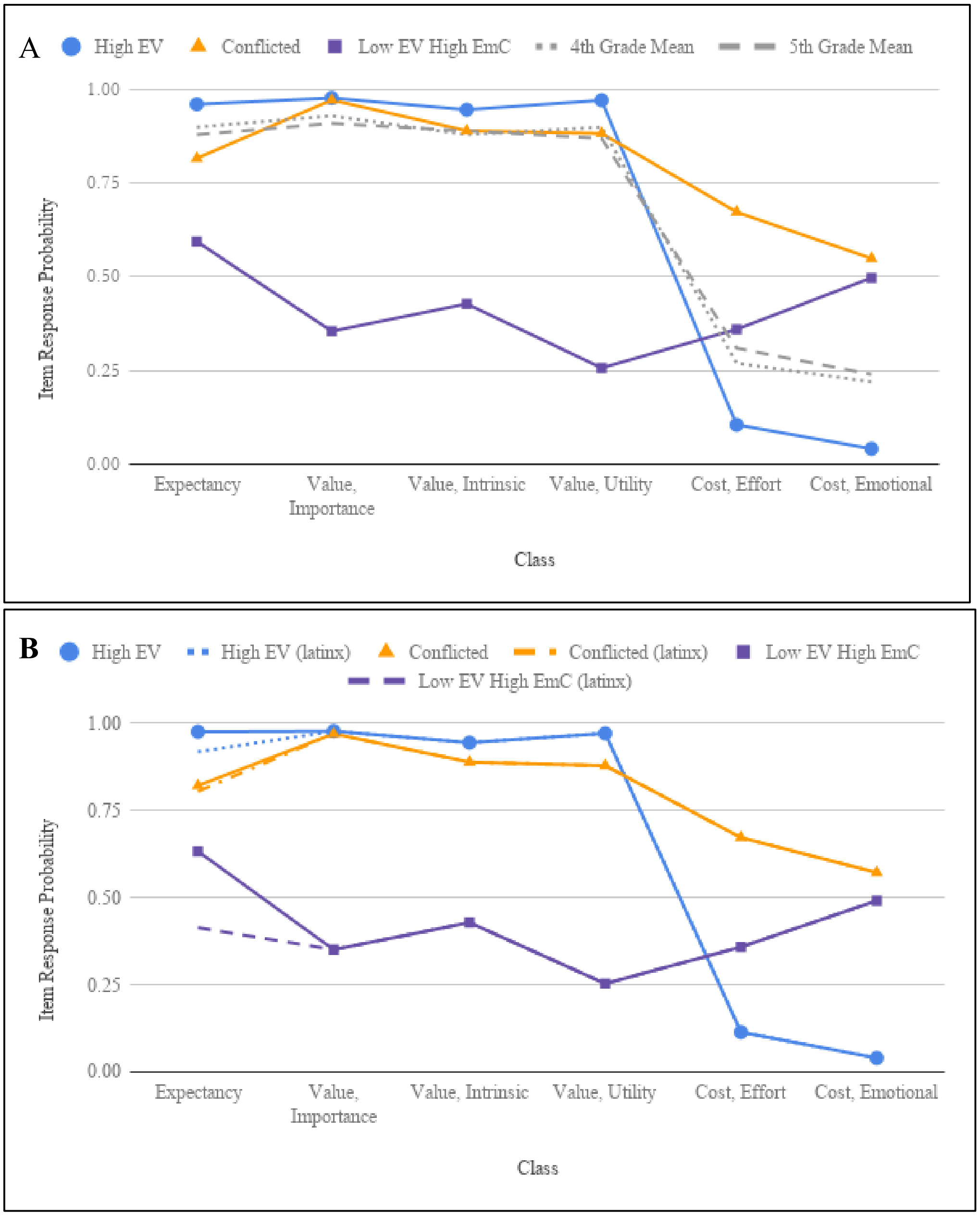

Figure 4.4 Latent statuses of the latent transition model.
A) Item response probability estimates from model 3I. B) Item response probabilities from model 3I Latinx variant.
Note: Note: E = Expectancy, V = Value, EmC = emotional cost

Chapter 5—Conclusion

The three studies described in this dissertation add to the growing body of person-centered research on expectancy-value-cost motivation (e.g., Andersen, 2013; Archambault et al., 2010; Chow et al., 2012; Conley, 2012; Linnenbrink-Garcia et al., 2018; Perez et al., 2019; Phelan et al., 2017; Wang et al., 2017). In the three studies described above, as in this prior person-centered research, a small number of qualitatively and substantively distinct classes provided the best fit to the data. In the aggregate, these latent classes aligned with the macro patterns of interrelations between task expectancy, task values, and perceived cost, and of relations between these motivation constructs and science achievement reported in past research (e.g., Conley, 2012; Eccles et al., 1983; Eccles & Wigfield, 1993; Kosovich et al., 2015).

Summary of Findings

In study 1, data collected as a part of the STEM Achievement in Baltimore Elementary Schools (SABES) project was used to identify and describe three latent science expectancy-value-cost motivation classes in 860 Black fifth graders. The classes consisted of a *High Expectancy and Value* (*High EV,* 73%) class; a *High Values and Perceived Costs, Moderate Expectancy* (*Conflicted,* 17%) class; and a *Low Expectancy and Value* (Low EV, 10%) class. While there were no differences in class membership based on gender, students receiving special education services were more likely to be in the *Conflicted* class relative to the *High EV* class.

In study 2 the relations between the latent classes described in study 1 and science achievement was explored. Higher prior achievement was predictive of being in the *High EV* class relative to the *Conflicted* class, while prior achievement had no significant relation with membership in the *High EV* class relative to the *Low EV* class. Membership in the *High EV* class was predictive of the higher subsequent science achievement; membership in the *Conflicted* class was predictive of the lowest science achievement; and membership in the *Low EV* class predicted achievement in between that of the other two classes.

The third study used latent transition analysis to regress latent class membership in fifth grade on membership in fourth grade for 1,706 fourth and fifth graders. A time-invariant three-class model was selected. The latent classes were similar to those described in study 1. Class membership was most stable in the *High EV* class, with 73% of students in this class in fourth grade estimated to be in the same class in fifth grade. The *Conflicted* class was less stable, with 56% of fourth grade members predicted to remain in the class in fifth grade, 37% predicted to transition to the *High EV* class, and 8% to the *Low EV* class. The *Low EV* class was the least stable, with 42% of fourth grade members predicted to remain in the class in fifth grade, 32% predicted to transition to the *High EV* class, and 26% to the *Conflicted* class.

Taken together, the results indicated that, in this sample of students, three patterns of expectancy-value-cost motivation in science are prevalent and each is more or less stable and more or less predictive of higher achievement. The most prevalent, *High EV*, is the most stable and adaptive, predicting future membership in the *High EV* class and higher achievement than the other two classes. While fourth grade class membership was not used to predict subsequent grades, the findings regarding achievement in fifth grade in conjunction with the latent transition analysis suggest that membership in this class increases propensity for higher grades which in turn increases propensity to be in this class which increases propensity for higher grades and so on. That this class was the most prevalent and stable in this sample of fourth and fifth graders who are predominantly from racial/ethnic groups that are historically underrepresented in STEM fields is a promising sign that a large portion of students in these schools are motivated toward science in a manner that, on average, results in higher achievement. Less promising is that the

Conflicted class was somewhat stable and the least adaptive in terms of science achievement. Lower prior grades resulted in students, on average, being more likely to be in the *Conflicted* class. In contrast, the *Low EV* class was the least stable and predicted achievement that was, on average, between that of students in the other two classes. Higher prior grades increased the probability of being in the *Low EV* class relative to the *Conflicted* class but there was no difference relative to the *High EV* class. More research is needed to determine if similar and/or other expectancy-value-cost motivation classes are common across samples.

Limitations

While latent class analysis has many benefits, as described above, it does present some limitations as well. Because latent class analysis relies on a contingency table of all possible survey responses, the more items that are added with more response choices, the larger the contingency table becomes. As the table becomes larger it becomes harder to find common patterns in responses. A large sample can be helpful. In the case of these studies, the sample size was large enough to allow the analyses described, but compromises were made to be able to estimate models. Models for which student responses to survey items were left as having five possible values would not converge. The same is true for trichotomized variable responses. As a result, student responses were dichotomized. By dichotomizing the variables information contained in the level of a student's response is lost. An additional limitation is introduced by the nature of the survey items. The items in these studies did not have a clear cut point. This results in reliance on the researcher's judgment on where to dichotomize the variable.

In many ways the unique nature of the sample of students in this study is an asset because samples in motivation research are infrequently comprised of elementary age students from underrepresented racial/ethnic groups. The specificity of this sample, a convenience sample consisting of students from 14 schools in one urban school district means that generalizations to all students cannot be made with confidence. This research must, then, be considered with the many other unique samples used in motivation research to begin to draw conclusions about student motivation, in general. Studies 1 and 2 were further limited because invariance testing indicated that different measurement models fit the data best for different groups of students. As a result only fifth grade Black students were retained for analysis. The larger sample size and the ability to estimate latent classes in fourth and fifth grade simultaneously in study 3 most likely contributed to avoiding this issue in study 3.

Finally, the survey used in these studies excludes some potentially important facets of expectancy-value-cost motivation. Among the major types of task values there was no item tapping attainment value. Recent research has indicated that task values may be described by many sub-constructs to the task values described in this study (Gaspard et al., 2015). In the realm of perceived costs these studies did not include items tapping loss of valued alternatives or outside effort cost. It could be argued that some of these constructs are not salient to elementary age children, as I have argued above for loss of valued alternatives. However this is not established in the literature and the omission here could obscure important variation in motivation. Despite these limitations, these studies contribute to the literature.

Value of a Person-Centered Approach

There are consistent macro patterns reported in expectancy-value-cost motivation research. The person-centered approach decomposes those patterns to reveal common intra-individual patterns that result in these macro patterns as well as the less common patterns that, at times, run counter to the expected relations between variables. For example, past research indicates that task expectancy and task values are positively associated with each other and are each negatively associated with perceived costs (e.g., Conley, 2012; Kosovich et al., 2015; Ruzek et al., in process). These patterns are apparent in the correlations of the dichotomized survey data in these studies (see, e.g., Table 4.2). When examining the common intra-individual patterns of responses to these items in study 1, for example, one can see important heterogeneity that is obscured by these variable-centered approaches. The *High EV* and *Low EV* class align with the patterns described above. When task expectancy is high, task values are also high, while perceived costs are low. When task expectancy is low, task values are low, while perceived costs are (relatively) high. The *Conflicted* class, however, provides an exception to this alignment. In this class both task values and perceived costs are (relatively) high. This class comprises only 17% of the sample, which is obscured in the aggregate by the 83% of the sample in the other two classes. By finding these common patterns across constructs within individuals, these unobserved heterogeneities can be found. For theories that posit multiple within-individual constructs this is especially valuable as illustrated by these studies.

Perceived Cost

Scholars have recently encouraged a renewed attention to perceived cost in expectancy-value motivation research (Barron & Hulleman, 2015; Flake et al., 2015). The results of these studies support this call. A key distinguishing characteristic of the *Conflicted* class, which predicted the lowest science achievement, was a much higher likelihood of endorsing perceived cost items. If perceived cost were excluded from this analysis, the *Conflicted* class would appear to be a class distinguished by moderate levels of task expectancy and moderate to high levels of task values, placing it firmly between the *High EV* and the *Low EV* class. Theory and prior research would predict that this middle-level motivation group would have achievement, on average, between that of the *High EV* and *Low EV* classes. However, in all cases the *Conflicted* class had lower achievement than the other two classes. This suggests that, as originally suggested by Eccles and colleagues (Eccles et al., 1983), one role of perceived cost is as a moderator of the influence of task values on achievement outcomes.

These studies also indicate that, in this sample, perceived costs co-occur with task expectancy and task values in particular patterns, which has implications for when perceived costs are most salient. For example, task values are relatively high in the *Conflicted* class, the only class with particularly high levels of perceived costs, especially emotional cost. In the *Low* EV class described in study 3, which included a larger sample of fourth and fifth graders, emotional cost was high and much higher than for the *High EV* class. In the one class with high levels of effort cost, the *Conflicted* class, task values were also high. In the two classes with higher effort cost, task expectancy was lower. This may indicate different types of cost are salient for different reasons. Emotional cost, for example, in the form of being stressed out by science class, may be most salient when valuing a task, while effort cost may be most salient when task expectancy is low (or visa versa). There could also be other causal explanations including influence of other cognitive constructs and/or contextual factors not considered here. More research that includes measures of perceived cost is warranted in order to build our knowledge of how perceived cost operates in conjunction with task expectancy and task values within individuals.

Practical Applications

The motivation survey administered in these studies is part of a larger effort to create short easy-to-implement motivation surveys that are also easy to interpret (Kosovich, Hulleman, & Barron, 2018; Kosovich et al., 2015). The evidence in the studies described here demonstrates how a small number of survey items can provide useful information about a student's motivation. That only three classes were found can simplify the results and help teachers to assess which students are in less adaptive motivational states and to inform what type of intervention might be best suited for each particular student.

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Biography

David McKinney was born in Tarzana, California on June 16th, 1983 to Ruth and Brian McKinney. David attended the California Institute of Technology where he studied biology and worked in the plant genetics and development lab of Dr. Elliot Meyerowitz as an undergraduate. He then attended Teachers College at Columbia University where he earned a masters degree in Secondary Science Teaching with a focus in Biology. He remained in New York City where he taught middle school science for one year at Frederick Douglas Academy V and for seven years at Isaac Newton Middle School. He also taught 6th grade math for four years while at Isaac Newton Middle School. In 2014 he transitioned to his doctoral studies at the Johns Hopkins University School of Education. He has worked on the STEM Achievement in Baltimore City Schools project and the Early Education Data Collaborative while at the School of Education.